pandas: powerful Python data analysis toolkit

Release 1.2.2

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Useful links: Binary Installers | Source Repository | Issues & Ideas | Q&A Support | Mailing List

`pandas` is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language.

To the getting started guides

To the user guide

To the reference guide

To the development guide

CHAPTER

ONE

GETTING STARTED

1.1 Installation

pandas is part of the Anaconda distribution and can be installed with Anaconda or Miniconda:

```
conda install pandas
```

pandas can be installed via pip from PyPI.

```
pip install pandas
```

Learn more

1.2 Intro to pandas

Straight to tutorial...

When working with tabular data, such as data stored in spreadsheets or databases, pandas is the right tool for you. pandas will help you to explore, clean and process your data. In pandas, a data table is called a `DataFrame`.

To introduction tutorial

To user guide

Straight to tutorial...

pandas supports the integration with many file formats or data sources out of the box (csv, excel, sql, json, parquet,...). Importing data from each of these data sources is provided by function with the prefix `read_*`. Similarly, the `to_*` methods are used to store data.

To introduction tutorial

To user guide

Straight to tutorial...

Selecting or filtering specific rows and/or columns? Filtering the data on a condition? Methods for slicing, selecting, and extracting the data you need are available in pandas.

To introduction tutorial

To user guide

Straight to tutorial...

pandas provides plotting your data out of the box, using the power of Matplotlib. You can pick the plot type (scatter, bar, boxplot,...) corresponding to your data.

To introduction tutorial

To user guide

Straight to tutorial...

There is no need to loop over all rows of your data table to do calculations. Data manipulations on a column work elementwise. Adding a column to a `DataFrame` based on existing data in other columns is straightforward.

To introduction tutorial

To user guide

Straight to tutorial...

Basic statistics (mean, median, min, max, counts...) are easily calculable. These or custom aggregations can be applied on the entire data set, a sliding window of the data or grouped by categories. The latter is also known as the split-apply-combine approach.

To introduction tutorial

To user guide

Straight to tutorial...

Change the structure of your data table in multiple ways. You can `melt()` your data table from wide to long/tidy form or `pivot()` from long to wide format. With aggregations built-in, a pivot table is created with a single command.

To introduction tutorial

To user guide

Straight to tutorial...

Multiple tables can be concatenated both column wise as row wise and database-like join/merge operations are provided to combine multiple tables of data.

To introduction tutorial

To user guide

Straight to tutorial...

pandas has great support for time series and has an extensive set of tools for working with dates, times, and time-indexed data.

To introduction tutorial

To user guide

Straight to tutorial...

Data sets do not only contain numerical data. pandas provides a wide range of functions to clean textual data and extract useful information from it.

To introduction tutorial

To user guide

1.3 Coming from...

Are you familiar with other software for manipulating tablular data? Learn the pandas-equivalent operations compared to software you already know:

Learn more

Learn more

Learn more

Learn more

1.4 Tutorials

For a quick overview of pandas functionality, see *10 Minutes to pandas*.

You can also reference the pandas cheat sheet for a succinct guide for manipulating data with pandas.

The community produces a wide variety of tutorials available online. Some of the material is enlisted in the community contributed *Community tutorials*.

1.4.1 Installation

The easiest way to install pandas is to install it as part of the Anaconda distribution, a cross platform distribution for data analysis and scientific computing. This is the recommended installation method for most users.

Instructions for installing from source, PyPI, ActivePython, various Linux distributions, or a development version are also provided.

Python version support

Officially Python 3.7.1 and above, 3.8, and 3.9.

Installing pandas

Installing with Anaconda

Installing pandas and the rest of the NumPy and SciPy stack can be a little difficult for inexperienced users.

The simplest way to install not only pandas, but Python and the most popular packages that make up the SciPy stack (IPython, NumPy, Matplotlib, ...) is with Anaconda, a cross-platform (Linux, macOS, Windows) Python distribution for data analytics and scientific computing.

After running the installer, the user will have access to pandas and the rest of the SciPy stack without needing to install anything else, and without needing to wait for any software to be compiled.

Installation instructions for Anaconda can be found here.

A full list of the packages available as part of the Anaconda distribution can be found here.

Another advantage to installing Anaconda is that you don't need admin rights to install it. Anaconda can install in the user's home directory, which makes it trivial to delete Anaconda if you decide (just delete that folder).

Installing with Miniconda

The previous section outlined how to get pandas installed as part of the Anaconda distribution. However this approach means you will install well over one hundred packages and involves downloading the installer which is a few hundred megabytes in size.

If you want to have more control on which packages, or have a limited internet bandwidth, then installing pandas with Miniconda may be a better solution.

Conda is the package manager that the Anaconda distribution is built upon. It is a package manager that is both cross-platform and language agnostic (it can play a similar role to a pip and virtualenv combination).

Miniconda allows you to create a minimal self contained Python installation, and then use the Conda command to install additional packages.

First you will need Conda to be installed and downloading and running the Miniconda will do this for you. The installer can be found here

The next step is to create a new conda environment. A conda environment is like a virtualenv that allows you to specify a specific version of Python and set of libraries. Run the following commands from a terminal window:

```
conda create -n name_of_my_env python
```

This will create a minimal environment with only Python installed in it. To put your self inside this environment run:

```
source activate name_of_my_env
```

On Windows the command is:

```
activate name_of_my_env
```

The final step required is to install pandas. This can be done with the following command:

```
conda install pandas
```

To install a specific pandas version:

```
conda install pandas=0.20.3
```

To install other packages, IPython for example:

```
conda install ipython
```

To install the full Anaconda distribution:

```
conda install anaconda
```

If you need packages that are available to pip but not conda, then install pip, and then use pip to install those packages:

```
conda install pip
pip install django
```

Installing from PyPI

pandas can be installed via pip from PyPI.

```
pip install pandas
```

Installing with ActivePython

Installation instructions for ActivePython can be found here. Versions 2.7, 3.5 and 3.6 include pandas.

Installing using your Linux distribution's package manager.

The commands in this table will install pandas for Python 3 from your distribution.

Distribution	Status	Download / Repository Link	Install method
Debian	stable	official Debian repository	`sudo apt-get install python3-pandas`
Debian & Ubuntu	unstable (latest packages)	NeuroDebian	`sudo apt-get install python3-pandas`
Ubuntu	stable	official Ubuntu repository	`sudo apt-get install python3-pandas`
OpenSuse	stable	OpenSuse Repository	`zypper in python3-pandas`
Fedora	stable	official Fedora repository	`dnf install python3-pandas`
Centos/RHEL	stable	EPEL repository	`yum install python3-pandas`

However, the packages in the linux package managers are often a few versions behind, so to get the newest version of pandas, it's recommended to install using the `pip` or `conda` methods described above.

Handling ImportErrors

If you encounter an ImportError, it usually means that Python couldn't find pandas in the list of available libraries. Python internally has a list of directories it searches through, to find packages. You can obtain these directories with:

```
import sys
sys.path
```

One way you could be encountering this error is if you have multiple Python installations on your system and you don't have pandas installed in the Python installation you're currently using. In Linux/Mac you can run `which python` on your terminal and it will tell you which Python installation you're using. If it's something like "/usr/bin/python", you're using the Python from the system, which is not recommended.

It is highly recommended to use `conda`, for quick installation and for package and dependency updates. You can find simple installation instructions for pandas in this document: `installation instructions </getting_started.html>`.

Installing from source

See the *contributing guide* for complete instructions on building from the git source tree. Further, see *creating a development environment* if you wish to create a pandas development environment.

Running the test suite

pandas is equipped with an exhaustive set of unit tests, covering about 97% of the code base as of this writing. To run it on your machine to verify that everything is working (and that you have all of the dependencies, soft and hard, installed), make sure you have pytest >= 5.0.1 and Hypothesis >= 3.58, then run:

```
>>> pd.test()
running: pytest --skip-slow --skip-network C:\Users\TP\Anaconda3\envs\py36\lib\site-
↪packages\pandas
============================= test session starts ==============================
platform win32 -- Python 3.6.2, pytest-3.6.0, py-1.4.34, pluggy-0.4.0
rootdir: C:\Users\TP\Documents\Python\pandasdev\pandas, inifile: setup.cfg
collected 12145 items / 3 skipped

..................................................................S......
........S.......................................................................
........................................................................

==================== 12130 passed, 12 skipped in 368.339 seconds =====================
```

Dependencies

Package	Minimum supported version
setuptools	24.2.0
NumPy	1.16.5
python-dateutil	2.7.3
pytz	2017.3

Recommended dependencies

- numexpr: for accelerating certain numerical operations. `numexpr` uses multiple cores as well as smart chunking and caching to achieve large speedups. If installed, must be Version 2.6.8 or higher.
- bottleneck: for accelerating certain types of `nan` evaluations. `bottleneck` uses specialized cython routines to achieve large speedups. If installed, must be Version 1.2.1 or higher.

Note: You are highly encouraged to install these libraries, as they provide speed improvements, especially when working with large data sets.

Optional dependencies

pandas has many optional dependencies that are only used for specific methods. For example, *pandas.read_hdf()* requires the `pytables` package, while *DataFrame.to_markdown()* requires the `tabulate` package. If the optional dependency is not installed, pandas will raise an `ImportError` when the method requiring that dependency is called.

Dependency	Minimum Version	Notes
BeautifulSoup4	4.6.0	HTML parser for read_html (see *note*)
Jinja2	2.10	Conditional formatting with DataFrame.style
PyQt4		Clipboard I/O
PyQt5		Clipboard I/O
PyTables	3.5.1	HDF5-based reading / writing
SQLAlchemy	1.3.0	SQL support for databases other than sqlite
SciPy	1.12.0	Miscellaneous statistical functions
xlsxwriter	1.0.2	Excel writing
blosc	1.17.0	Compression for HDF5
fsspec	0.7.4	Handling files aside from local and HTTP
fastparquet	0.4.0	Parquet reading / writing
gcsfs	0.6.0	Google Cloud Storage access
html5lib	1.0.1	HTML parser for read_html (see *note*)
lxml	4.3.0	HTML parser for read_html (see *note*)
matplotlib	2.2.3	Visualization
numba	0.46.0	Alternative execution engine for rolling operations
openpyxl	2.6.0	Reading / writing for xlsx files
pandas-gbq	0.12.0	Google Big Query access
psycopg2	2.7	PostgreSQL engine for sqlalchemy
pyarrow	0.15.0	Parquet, ORC, and feather reading / writing
pymysql	0.8.1	MySQL engine for sqlalchemy
pyreadstat		SPSS files (.sav) reading
pyxlsb	1.0.6	Reading for xlsb files
qtpy		Clipboard I/O
s3fs	0.4.0	Amazon S3 access
tabulate	0.8.3	Printing in Markdown-friendly format (see tabulate)
xarray	0.12.3	pandas-like API for N-dimensional data
xclip		Clipboard I/O on linux
xlrd	1.2.0	Excel reading
xlwt	1.3.0	Excel writing
xsel		Clipboard I/O on linux
zlib		Compression for HDF5

Optional dependencies for parsing HTML

One of the following combinations of libraries is needed to use the top-level *read_html()* function:

- BeautifulSoup4 and html5lib
- BeautifulSoup4 and lxml
- BeautifulSoup4 and html5lib and lxml
- Only lxml, although see *HTML Table Parsing* for reasons as to why you should probably **not** take this approach.

Warning:

- if you install BeautifulSoup4 you must install either lxml or html5lib or both. `read_html()` will **not** work with *only* BeautifulSoup4 installed.
- You are highly encouraged to read *HTML Table Parsing gotchas*. It explains issues surrounding the installation and usage of the above three libraries.

1.4.2 Package overview

pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with "relational" or "labeled" data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, **real-world** data analysis in Python. Additionally, it has the broader goal of becoming **the most powerful and flexible open source data analysis/manipulation tool available in any language**. It is already well on its way toward this goal.

pandas is well suited for many different kinds of data:

- Tabular data with heterogeneously-typed columns, as in an SQL table or Excel spreadsheet
- Ordered and unordered (not necessarily fixed-frequency) time series data.
- Arbitrary matrix data (homogeneously typed or heterogeneous) with row and column labels
- Any other form of observational / statistical data sets. The data need not be labeled at all to be placed into a pandas data structure

The two primary data structures of pandas, `Series` (1-dimensional) and `DataFrame` (2-dimensional), handle the vast majority of typical use cases in finance, statistics, social science, and many areas of engineering. For R users, `DataFrame` provides everything that R's `data.frame` provides and much more. pandas is built on top of NumPy and is intended to integrate well within a scientific computing environment with many other 3rd party libraries.

Here are just a few of the things that pandas does well:

- Easy handling of **missing data** (represented as NaN) in floating point as well as non-floating point data
- Size mutability: columns can be **inserted and deleted** from DataFrame and higher dimensional objects
- Automatic and explicit **data alignment**: objects can be explicitly aligned to a set of labels, or the user can simply ignore the labels and let `Series`, `DataFrame`, etc. automatically align the data for you in computations
- Powerful, flexible **group by** functionality to perform split-apply-combine operations on data sets, for both aggregating and transforming data
- Make it **easy to convert** ragged, differently-indexed data in other Python and NumPy data structures into DataFrame objects
- Intelligent label-based **slicing**, **fancy indexing**, and **subsetting** of large data sets
- Intuitive **merging** and **joining** data sets
- Flexible **reshaping** and pivoting of data sets
- **Hierarchical** labeling of axes (possible to have multiple labels per tick)
- Robust IO tools for loading data from **flat files** (CSV and delimited), Excel files, databases, and saving / loading data from the ultrafast **HDF5 format**
- **Time series**-specific functionality: date range generation and frequency conversion, moving window statistics, date shifting, and lagging.

Many of these principles are here to address the shortcomings frequently experienced using other languages / scientific research environments. For data scientists, working with data is typically divided into multiple stages: munging and cleaning data, analyzing / modeling it, then organizing the results of the analysis into a form suitable for plotting or tabular display. pandas is the ideal tool for all of these tasks.

Some other notes

- pandas is **fast**. Many of the low-level algorithmic bits have been extensively tweaked in Cython code. However, as with anything else generalization usually sacrifices performance. So if you focus on one feature for your application you may be able to create a faster specialized tool.
- pandas is a dependency of statsmodels, making it an important part of the statistical computing ecosystem in Python.
- pandas has been used extensively in production in financial applications.

Data structures

Dimensions	Name	Description
1	Series	1D labeled homogeneously-typed array
2	DataFrame	General 2D labeled, size-mutable tabular structure with potentially heterogeneously-typed column

Why more than one data structure?

The best way to think about the pandas data structures is as flexible containers for lower dimensional data. For example, DataFrame is a container for Series, and Series is a container for scalars. We would like to be able to insert and remove objects from these containers in a dictionary-like fashion.

Also, we would like sensible default behaviors for the common API functions which take into account the typical orientation of time series and cross-sectional data sets. When using the N-dimensional array (ndarrays) to store 2- and 3-dimensional data, a burden is placed on the user to consider the orientation of the data set when writing functions; axes are considered more or less equivalent (except when C- or Fortran-contiguousness matters for performance). In pandas, the axes are intended to lend more semantic meaning to the data; i.e., for a particular data set, there is likely to be a "right" way to orient the data. The goal, then, is to reduce the amount of mental effort required to code up data transformations in downstream functions.

For example, with tabular data (DataFrame) it is more semantically helpful to think of the **index** (the rows) and the **columns** rather than axis 0 and axis 1. Iterating through the columns of the DataFrame thus results in more readable code:

```
for col in df.columns:
    series = df[col]
    # do something with series
```

Mutability and copying of data

All pandas data structures are value-mutable (the values they contain can be altered) but not always size-mutable. The length of a Series cannot be changed, but, for example, columns can be inserted into a DataFrame. However, the vast majority of methods produce new objects and leave the input data untouched. In general we like to **favor immutability** where sensible.

Getting support

The first stop for pandas issues and ideas is the Github Issue Tracker. If you have a general question, pandas community experts can answer through Stack Overflow.

Community

pandas is actively supported today by a community of like-minded individuals around the world who contribute their valuable time and energy to help make open source pandas possible. Thanks to all of our contributors.

If you're interested in contributing, please visit the *contributing guide*.

pandas is a NumFOCUS sponsored project. This will help ensure the success of the development of pandas as a world-class open-source project and makes it possible to donate to the project.

Project governance

The governance process that pandas project has used informally since its inception in 2008 is formalized in Project Governance documents. The documents clarify how decisions are made and how the various elements of our community interact, including the relationship between open source collaborative development and work that may be funded by for-profit or non-profit entities.

Wes McKinney is the Benevolent Dictator for Life (BDFL).

Development team

The list of the Core Team members and more detailed information can be found on the people's page of the governance repo.

Institutional partners

The information about current institutional partners can be found on pandas website page.

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```
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OF THIS SOFTWARE, EVEN IF ADVISED OF THE POSSIBILITY OF SUCH DAMAGE.
```

1.4.3 Getting started tutorials

What kind of data does pandas handle?

I want to start using pandas

```
In [1]: import pandas as pd
```

To load the pandas package and start working with it, import the package. The community agreed alias for pandas is `pd`, so loading pandas as `pd` is assumed standard practice for all of the pandas documentation.

pandas data table representation

I want to store passenger data of the Titanic. For a number of passengers, I know the name (characters), age (integers) and sex (male/female) data.

```
In [2]: df = pd.DataFrame(
   ...:     {
   ...:         "Name": [
   ...:             "Braund, Mr. Owen Harris",
   ...:             "Allen, Mr. William Henry",
   ...:             "Bonnell, Miss. Elizabeth",
   ...:         ],
   ...:         "Age": [22, 35, 58],
   ...:         "Sex": ["male", "male", "female"],
   ...:     }
   ...: )
```

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```
   ...:

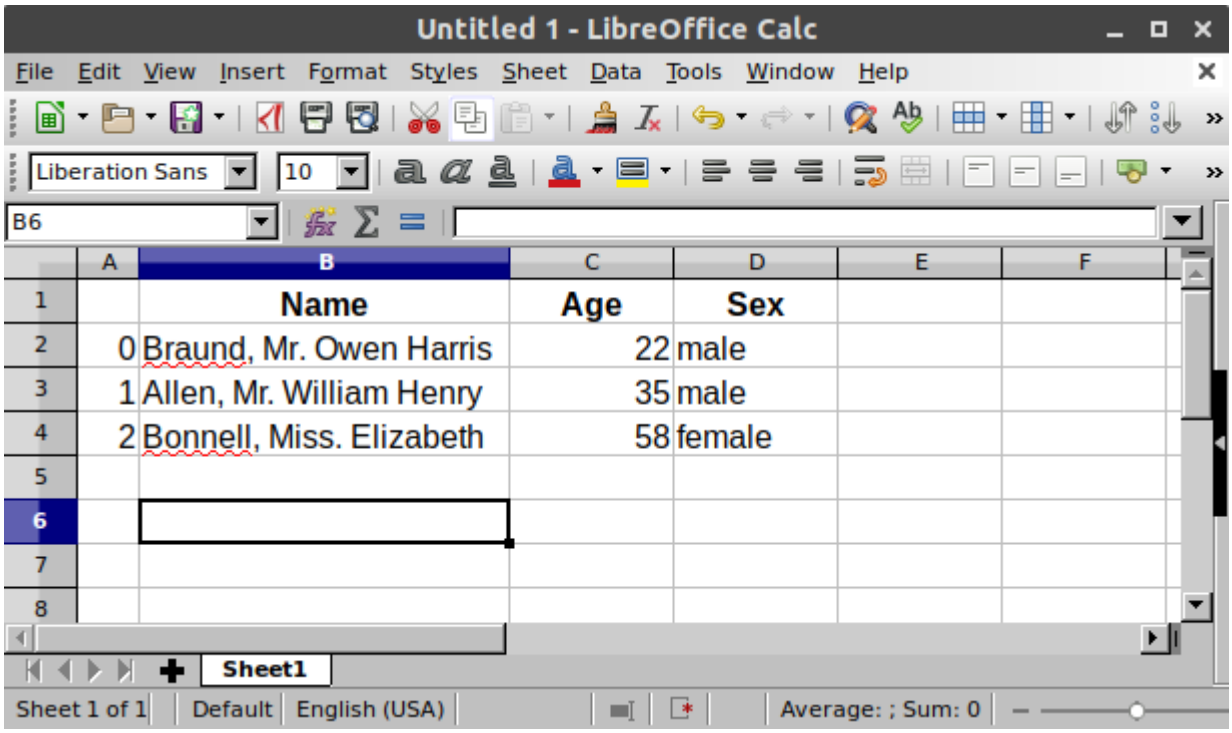
In [3]: df
Out[3]:
                        Name  Age     Sex
0    Braund, Mr. Owen Harris   22    male
1  Allen, Mr. William Henry   35    male
2  Bonnell, Miss. Elizabeth   58  female
```

To manually store data in a table, create a `DataFrame`. When using a Python dictionary of lists, the dictionary keys will be used as column headers and the values in each list as columns of the `DataFrame`.

A *`DataFrame`* is a 2-dimensional data structure that can store data of different types (including characters, integers, floating point values, categorical data and more) in columns. It is similar to a spreadsheet, a SQL table or the `data.frame` in R.

- The table has 3 columns, each of them with a column label. The column labels are respectively `Name`, `Age` and `Sex`.
- The column `Name` consists of textual data with each value a string, the column `Age` are numbers and the column `Sex` is textual data.

In spreadsheet software, the table representation of our data would look very similar:



Each column in a `DataFrame` is a `Series`

I'm just interested in working with the data in the column `Age`

```
In [4]: df["Age"]
Out[4]:
0    22
1    35
2    58
Name: Age, dtype: int64
```

When selecting a single column of a pandas *`DataFrame`*, the result is a pandas *`Series`*. To select the column, use the column label in between square brackets `[]`.

Note: If you are familiar to Python dictionaries, the selection of a single column is very similar to selection of dictionary values based on the key.

You can create a `Series` from scratch as well:

```
In [5]: ages = pd.Series([22, 35, 58], name="Age")

In [6]: ages
Out[6]:
0    22
1    35
2    58
Name: Age, dtype: int64
```

A pandas `Series` has no column labels, as it is just a single column of a `DataFrame`. A Series does have row labels.

Do something with a DataFrame or Series

I want to know the maximum Age of the passengers

We can do this on the `DataFrame` by selecting the `Age` column and applying `max()`:

```
In [7]: df["Age"].max()
Out[7]: 58
```

Or to the `Series`:

```
In [8]: ages.max()
Out[8]: 58
```

As illustrated by the `max()` method, you can *do* things with a `DataFrame` or `Series`. pandas provides a lot of functionalities, each of them a *method* you can apply to a `DataFrame` or `Series`. As methods are functions, do not forget to use parentheses `()`.

I'm interested in some basic statistics of the numerical data of my data table

```
In [9]: df.describe()
Out[9]:
```

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```
             Age
count   3.000000
mean   38.333333
std    18.230012
min    22.000000
25%    28.500000
50%    35.000000
75%    46.500000
max    58.000000
```

The *describe()* method provides a quick overview of the numerical data in a DataFrame. As the Name and Sex columns are textual data, these are by default not taken into account by the *describe()* method.

Many pandas operations return a DataFrame or a Series. The *describe()* method is an example of a pandas operation returning a pandas Series.

Check more options on describe in the user guide section about *aggregations with describe*

Note: This is just a starting point. Similar to spreadsheet software, pandas represents data as a table with columns and rows. Apart from the representation, also the data manipulations and calculations you would do in spreadsheet software are supported by pandas. Continue reading the next tutorials to get started!

- Import the package, aka `import pandas as pd`
- A table of data is stored as a pandas DataFrame
- Each column in a DataFrame is a Series
- You can do things by applying a method to a DataFrame or Series

A more extended explanation to DataFrame and Series is provided in the *introduction to data structures*.

```
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

How do I read and write tabular data?

I want to analyze the Titanic passenger data, available as a CSV file.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

pandas provides the *read_csv()* function to read data stored as a csv file into a pandas DataFrame. pandas supports many different file formats or data sources out of the box (csv, excel, sql, json, parquet, ...), each of them with the prefix read_*.

Make sure to always have a check on the data after reading in the data. When displaying a DataFrame, the first and last 5 rows will be shown by default:

```
In [3]: titanic
Out[3]:
     PassengerId  Survived  Pclass  ...     Fare Cabin  Embarked
0              1         0       3  ...   7.2500   NaN         S
1              2         1       1  ...  71.2833   C85         C
2              3         1       3  ...   7.9250   NaN         S
3              4         1       1  ...  53.1000  C123         S
4              5         0       3  ...   8.0500   NaN         S
..           ...       ...     ...  ...      ...   ...       ...
886          887         0       2  ...  13.0000   NaN         S
887          888         1       1  ...  30.0000   B42         S
888          889         0       3  ...  23.4500   NaN         S
889          890         1       1  ...  30.0000  C148         C
890          891         0       3  ...   7.7500   NaN         Q

[891 rows x 12 columns]
```

I want to see the first 8 rows of a pandas DataFrame.

```
In [4]: titanic.head(8)
Out[4]:
   PassengerId  Survived  Pclass                                               Name  .
↪..             Ticket     Fare  Cabin  Embarked
0            1         0       3                            Braund, Mr. Owen Harris  .
↪..          A/5 21171   7.2500    NaN         S
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  .
↪..           PC 17599  71.2833    C85         C
2            3         1       3                             Heikkinen, Miss. Laina  .
↪..   STON/O2. 3101282   7.9250    NaN         S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  .
↪..             113803  53.1000   C123         S
4            5         0       3                           Allen, Mr. William Henry  .
↪..             373450   8.0500    NaN         S
5            6         0       3                                   Moran, Mr. James  .
↪..             330877   8.4583    NaN         Q
6            7         0       1                            McCarthy, Mr. Timothy J  .
↪..              17463  51.8625    E46         S
7            8         0       3                     Palsson, Master. Gosta Leonard  .
↪..             349909  21.0750    NaN         S

[8 rows x 12 columns]
```

To see the first N rows of a DataFrame, use the *head()* method with the required number of rows (in this case 8) as argument.

Note: Interested in the last N rows instead? pandas also provides a *tail()* method. For example, `titanic.tail(10)` will return the last 10 rows of the DataFrame.

A check on how pandas interpreted each of the column data types can be done by requesting the pandas `dtypes` attribute:

```
In [5]: titanic.dtypes
Out[5]:
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

For each of the columns, the used data type is enlisted. The data types in this `DataFrame` are integers (`int64`), floats (`float64`) and strings (`object`).

Note: When asking for the `dtypes`, no brackets are used! `dtypes` is an attribute of a `DataFrame` and `Series`. Attributes of `DataFrame` or `Series` do not need brackets. Attributes represent a characteristic of a `DataFrame`/`Series`, whereas a method (which requires brackets) *do* something with the `DataFrame`/`Series` as introduced in the *first tutorial*.

My colleague requested the Titanic data as a spreadsheet.

```
In [6]: titanic.to_excel("titanic.xlsx", sheet_name="passengers", index=False)
```

Whereas `read_*` functions are used to read data to pandas, the `to_*` methods are used to store data. The *to_excel()* method stores the data as an excel file. In the example here, the `sheet_name` is named *passengers* instead of the default *Sheet1*. By setting `index=False` the row index labels are not saved in the spreadsheet.

The equivalent read function `read_excel()` will reload the data to a `DataFrame`:

```
In [7]: titanic = pd.read_excel("titanic.xlsx", sheet_name="passengers")
```

```
In [8]: titanic.head()
Out[8]:
   PassengerId  Survived  Pclass                                               Name  .
↪..             Ticket     Fare  Cabin  Embarked
0            1         0       3                            Braund, Mr. Owen Harris  .
↪..          A/5 21171   7.2500    NaN         S
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  .
↪..           PC 17599  71.2833    C85         C
2            3         1       3                             Heikkinen, Miss. Laina  .
↪..  STON/O2. 3101282   7.9250    NaN         S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  .
↪..             113803  53.1000   C123         S
```

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```
4            5         0       3                              Allen, Mr. William Henry  .
↪..            373450   8.0500    NaN         S

[5 rows x 12 columns]
```

I'm interested in a technical summary of a `DataFrame`

```
In [9]: titanic.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

The method *`info()`* provides technical information about a `DataFrame`, so let's explain the output in more detail:

- It is indeed a *`DataFrame`*.
- There are 891 entries, i.e. 891 rows.
- Each row has a row label (aka the `index`) with values ranging from 0 to 890.
- The table has 12 columns. Most columns have a value for each of the rows (all 891 values are `non-null`). Some columns do have missing values and less than 891 `non-null` values.
- The columns `Name`, `Sex`, `Cabin` and `Embarked` consists of textual data (strings, aka `object`). The other columns are numerical data with some of them whole numbers (aka `integer`) and others are real numbers (aka `float`).
- The kind of data (characters, integers,...) in the different columns are summarized by listing the `dtypes`.
- The approximate amount of RAM used to hold the DataFrame is provided as well.
- Getting data in to pandas from many different file formats or data sources is supported by `read_*` functions.
- Exporting data out of pandas is provided by different `to_*`methods.
- The `head`/`tail`/`info` methods and the `dtypes` attribute are convenient for a first check.

For a complete overview of the input and output possibilities from and to pandas, see the user guide section about *reader and writer functions*.

```
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.

- Survived: This feature has value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passengers have siblings and spouses.
- Parch: Whether a passenger is alone or has a family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")

In [3]: titanic.head()
Out[3]:
   PassengerId  Survived  Pclass                                                Name  .
↪..            Ticket     Fare  Cabin  Embarked
0            1         0       3                            Braund, Mr. Owen Harris  .
↪..         A/5 21171   7.2500    NaN         S
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  .
↪..          PC 17599  71.2833    C85         C
2            3         1       3                             Heikkinen, Miss. Laina  .
↪..  STON/O2. 3101282   7.9250    NaN         S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  .
↪..           113803  53.1000   C123         S
4            5         0       3                           Allen, Mr. William Henry  .
↪..           373450   8.0500    NaN         S

[5 rows x 12 columns]
```

How do I select a subset of a `DataFrame`?

How do I select specific columns from a `DataFrame`?

I'm interested in the age of the Titanic passengers.

```
In [4]: ages = titanic["Age"]

In [5]: ages.head()
Out[5]:
0    22.0
1    38.0
2    26.0
3    35.0
4    35.0
Name: Age, dtype: float64
```

To select a single column, use square brackets `[]` with the column name of the column of interest.

Each column in a *DataFrame* is a *Series*. As a single column is selected, the returned object is a pandas *Series*. We can verify this by checking the type of the output:

```
In [6]: type(titanic["Age"])
Out[6]: pandas.core.series.Series
```

And have a look at the `shape` of the output:

```
In [7]: titanic["Age"].shape
Out[7]: (891,)
```

DataFrame.shape is an attribute (remember *tutorial on reading and writing*, do not use parentheses for attributes) of a pandas `Series` and `DataFrame` containing the number of rows and columns: *(nrows, ncolumns)*. A pandas Series is 1-dimensional and only the number of rows is returned.

I'm interested in the age and sex of the Titanic passengers.

```
In [8]: age_sex = titanic[["Age", "Sex"]]

In [9]: age_sex.head()
Out[9]:
    Age     Sex
0  22.0    male
1  38.0  female
2  26.0  female
3  35.0  female
4  35.0    male
```

To select multiple columns, use a list of column names within the selection brackets `[]`.

Note: The inner square brackets define a Python list with column names, whereas the outer brackets are used to select the data from a pandas `DataFrame` as seen in the previous example.

The returned data type is a pandas DataFrame:

```
In [10]: type(titanic[["Age", "Sex"]])
Out[10]: pandas.core.frame.DataFrame
```

```
In [11]: titanic[["Age", "Sex"]].shape
Out[11]: (891, 2)
```

The selection returned a `DataFrame` with 891 rows and 2 columns. Remember, a `DataFrame` is 2-dimensional with both a row and column dimension.

For basic information on indexing, see the user guide section on *indexing and selecting data*.

How do I filter specific rows from a DataFrame?

I'm interested in the passengers older than 35 years.

```
In [12]: above_35 = titanic[titanic["Age"] > 35]

In [13]: above_35.head()
Out[13]:
    PassengerId  Survived  Pclass                                                Name␣
↪...    Ticket     Fare  Cabin  Embarked
1             2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...␣
↪...  PC 17599  71.2833    C85         C
6             7         0       1                              McCarthy, Mr. Timothy J␣
↪...     17463  51.8625    E46         S
11           12         1       1                            Bonnell, Miss. Elizabeth␣
↪...    113783  26.5500   C103         S
13           14         0       3                          Andersson, Mr. Anders Johan␣
↪...    347082  31.2750    NaN         S
15           16         1       2                  Hewlett, Mrs. (Mary D Kingcome)  ␣
↪...    248706  16.0000    NaN         S

[5 rows x 12 columns]
```

To select rows based on a conditional expression, use a condition inside the selection brackets `[]`.

The condition inside the selection brackets `titanic["Age"] > 35` checks for which rows the `Age` column has a value larger than 35:

```
In [14]: titanic["Age"] > 35
Out[14]:
0      False
1       True
2      False
3      False
4      False
       ...
886    False
887    False
888    False
889    False
890    False
Name: Age, Length: 891, dtype: bool
```

The output of the conditional expression (>, but also ==, !=, <, <=,... would work) is actually a pandas `Series` of boolean values (either `True` or `False`) with the same number of rows as the original `DataFrame`. Such a `Series` of boolean values can be used to filter the `DataFrame` by putting it in between the selection brackets `[]`. Only rows for which the value is `True` will be selected.

We know from before that the original Titanic `DataFrame` consists of 891 rows. Let's have a look at the number of rows which satisfy the condition by checking the `shape` attribute of the resulting `DataFrame` `above_35`:

```
In [15]: above_35.shape
Out[15]: (217, 12)
```

I'm interested in the Titanic passengers from cabin class 2 and 3.

```
In [16]: class_23 = titanic[titanic["Pclass"].isin([2, 3])]

In [17]: class_23.head()
Out[17]:
   PassengerId  Survived  Pclass                                Name     Sex  ...  Parch ␣
↪          Ticket     Fare Cabin  Embarked
0            1         0       3         Braund, Mr. Owen Harris    male  ...      0 ␣
↪       A/5 21171   7.2500   NaN         S
2            3         1       3          Heikkinen, Miss. Laina  female  ...      0 ␣
↪STON/O2. 3101282   7.9250   NaN         S
4            5         0       3        Allen, Mr. William Henry    male  ...      0 ␣
↪          373450   8.0500   NaN         S
5            6         0       3                Moran, Mr. James    male  ...      0 ␣
↪          330877   8.4583   NaN         Q
7            8         0       3  Palsson, Master. Gosta Leonard    male  ...      1 ␣
↪          349909  21.0750   NaN         S

[5 rows x 12 columns]
```

Similar to the conditional expression, the *isin()* conditional function returns a `True` for each row the values are in the provided list. To filter the rows based on such a function, use the conditional function inside the selection brackets `[]`. In this case, the condition inside the selection brackets `titanic["Pclass"].isin([2, 3])` checks for which rows the `Pclass` column is either 2 or 3.

The above is equivalent to filtering by rows for which the class is either 2 or 3 and combining the two statements with an `|` (or) operator:

```
In [18]: class_23 = titanic[(titanic["Pclass"] == 2) | (titanic["Pclass"] == 3)]

In [19]: class_23.head()
Out[19]:
   PassengerId  Survived  Pclass                                Name     Sex  ...  Parch ␣
↪          Ticket     Fare Cabin  Embarked
0            1         0       3         Braund, Mr. Owen Harris    male  ...      0 ␣
↪       A/5 21171   7.2500   NaN         S
2            3         1       3          Heikkinen, Miss. Laina  female  ...      0 ␣
↪STON/O2. 3101282   7.9250   NaN         S
4            5         0       3        Allen, Mr. William Henry    male  ...      0 ␣
↪          373450   8.0500   NaN         S
5            6         0       3                Moran, Mr. James    male  ...      0 ␣
↪          330877   8.4583   NaN         Q
7            8         0       3  Palsson, Master. Gosta Leonard    male  ...      1 ␣
↪          349909  21.0750   NaN         S

[5 rows x 12 columns]
```

Note: When combining multiple conditional statements, each condition must be surrounded by parentheses `()`. Moreover, you can not use `or`/`and` but need to use the `or` operator `|` and the `and` operator `&`.

See the dedicated section in the user guide about *boolean indexing* or about the *isin function*.

I want to work with passenger data for which the age is known.

```
In [20]: age_no_na = titanic[titanic["Age"].notna()]

In [21]: age_no_na.head()
```

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```
Out[21]:
   PassengerId  Survived  Pclass                                                Name  .
↪..             Ticket     Fare  Cabin  Embarked
0            1         0       3                            Braund, Mr. Owen Harris  .
↪..          A/5 21171   7.2500    NaN         S
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  .
↪..           PC 17599  71.2833    C85         C
2            3         1       3                             Heikkinen, Miss. Laina  .
↪..  STON/O2. 3101282   7.9250    NaN         S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  .
↪..             113803  53.1000   C123         S
4            5         0       3                           Allen, Mr. William Henry  .
↪..             373450   8.0500    NaN         S

[5 rows x 12 columns]
```

The *notna()* conditional function returns a `True` for each row the values are not an `Null` value. As such, this can be combined with the selection brackets `[]` to filter the data table.

You might wonder what actually changed, as the first 5 lines are still the same values. One way to verify is to check if the shape has changed:

```
In [22]: age_no_na.shape
Out[22]: (714, 12)
```

For more dedicated functions on missing values, see the user guide section about *handling missing data*.

How do I select specific rows and columns from a `DataFrame`?

I'm interested in the names of the passengers older than 35 years.

```
In [23]: adult_names = titanic.loc[titanic["Age"] > 35, "Name"]

In [24]: adult_names.head()
Out[24]:
1     Cumings, Mrs. John Bradley (Florence Briggs Th...
6                               McCarthy, Mr. Timothy J
11                            Bonnell, Miss. Elizabeth
13                          Andersson, Mr. Anders Johan
15                      Hewlett, Mrs. (Mary D Kingcome)
Name: Name, dtype: object
```

In this case, a subset of both rows and columns is made in one go and just using selection brackets `[]` is not sufficient anymore. The `loc`/`iloc` operators are required in front of the selection brackets `[]`. When using `loc`/`iloc`, the part before the comma is the rows you want, and the part after the comma is the columns you want to select.

When using the column names, row labels or a condition expression, use the `loc` operator in front of the selection brackets `[]`. For both the part before and after the comma, you can use a single label, a list of labels, a slice of labels, a conditional expression or a colon. Using a colon specifies you want to select all rows or columns.

I'm interested in rows 10 till 25 and columns 3 to 5.

```
In [25]: titanic.iloc[9:25, 2:5]
Out[25]:
```

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```
    Pclass                                     Name     Sex
9        2  Nasser, Mrs. Nicholas (Adele Achem)  female
10       3      Sandstrom, Miss. Marguerite Rut  female
11       1             Bonnell, Miss. Elizabeth  female
12       3       Saundercock, Mr. William Henry    male
13       3          Andersson, Mr. Anders Johan    male
..     ...                                  ...     ...
20       2                Fynney, Mr. Joseph J    male
21       2               Beesley, Mr. Lawrence    male
22       3          McGowan, Miss. Anna "Annie"  female
23       1         Sloper, Mr. William Thompson    male
24       3        Palsson, Miss. Torborg Danira  female

[16 rows x 3 columns]
```

Again, a subset of both rows and columns is made in one go and just using selection brackets `[]` is not sufficient anymore. When specifically interested in certain rows and/or columns based on their position in the table, use the `iloc` operator in front of the selection brackets `[]`.

When selecting specific rows and/or columns with `loc` or `iloc`, new values can be assigned to the selected data. For example, to assign the name `anonymous` to the first 3 elements of the third column:

```
In [26]: titanic.iloc[0:3, 3] = "anonymous"

In [27]: titanic.head()
Out[27]:
   PassengerId  Survived  Pclass                                                 Name  ...  ␣
↪         Ticket     Fare  Cabin  Embarked
0            1         0       3                                        anonymous  ...  ␣
↪      A/5 21171   7.2500    NaN         S
1            2         1       1                                        anonymous  ...  ␣
↪       PC 17599  71.2833    C85         C
2            3         1       3                                        anonymous  ... ␣
↪STON/O2. 3101282   7.9250    NaN         S
3            4         1       1  Futrelle, Mrs. Jacques Heath (Lily May Peel)  ...  ␣
↪         113803  53.1000   C123         S
4            5         0       3                       Allen, Mr. William Henry  ...  ␣
↪         373450   8.0500    NaN         S

[5 rows x 12 columns]
```

See the user guide section on *different choices for indexing* to get more insight in the usage of `loc` and `iloc`.

- When selecting subsets of data, square brackets `[]` are used.
- Inside these brackets, you can use a single column/row label, a list of column/row labels, a slice of labels, a conditional expression or a colon.
- Select specific rows and/or columns using `loc` when using the row and column names
- Select specific rows and/or columns using `iloc` when using the positions in the table
- You can assign new values to a selection based on `loc`/`iloc`.

A full overview of indexing is provided in the user guide pages on *indexing and selecting data*.

```
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt
```

For this tutorial, air quality data about NO_2 is used, made available by openaq and using the py-openaq package. The `air_quality_no2.csv` data set provides NO_2 values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [3]: air_quality = pd.read_csv("data/air_quality_no2.csv", index_col=0, parse_
↪dates=True)

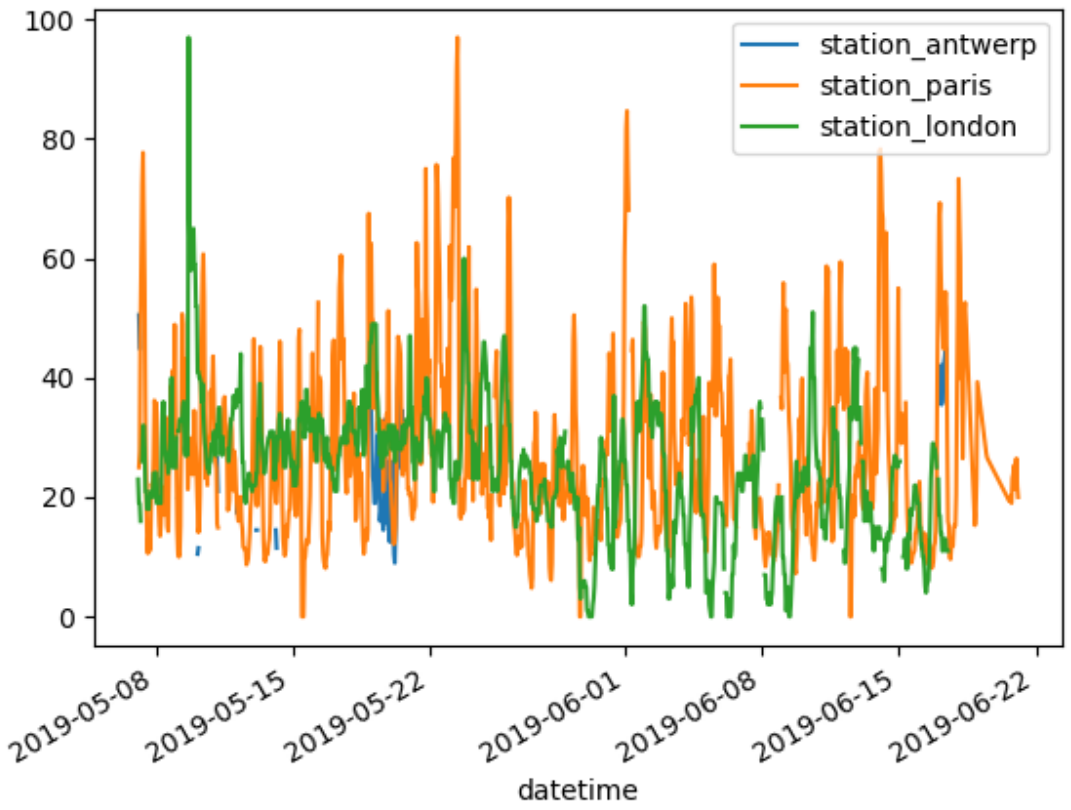
In [4]: air_quality.head()
Out[4]:
                     station_antwerp  station_paris  station_london
datetime
2019-05-07 02:00:00              NaN            NaN            23.0
2019-05-07 03:00:00             50.5           25.0            19.0
2019-05-07 04:00:00             45.0           27.7            19.0
2019-05-07 05:00:00              NaN           50.4            16.0
2019-05-07 06:00:00              NaN           61.9             NaN
```

Note: The usage of the `index_col` and `parse_dates` parameters of the `read_csv` function to define the first (0th) column as index of the resulting `DataFrame` and convert the dates in the column to *`Timestamp`* objects, respectively.

How to create plots in pandas?

I want a quick visual check of the data.

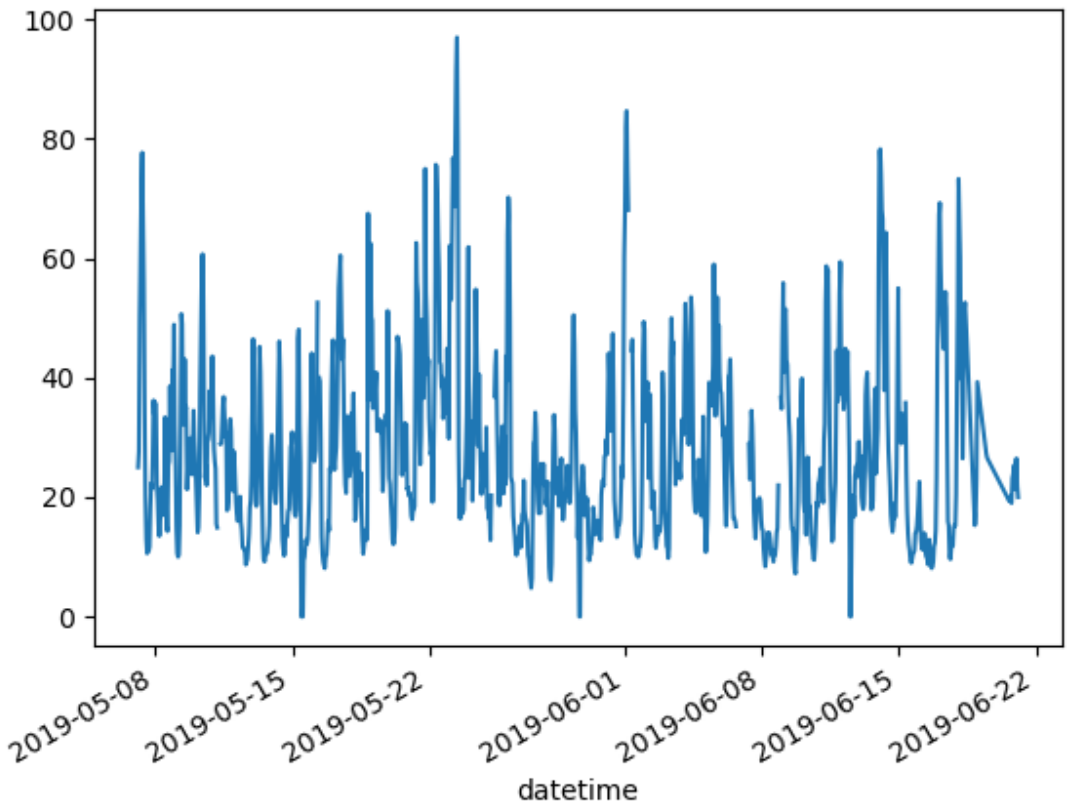
```
In [5]: air_quality.plot()
Out[5]: <AxesSubplot:xlabel='datetime'>
```



With a `DataFrame`, pandas creates by default one line plot for each of the columns with numeric data.

I want to plot only the columns of the data table with the data from Paris.

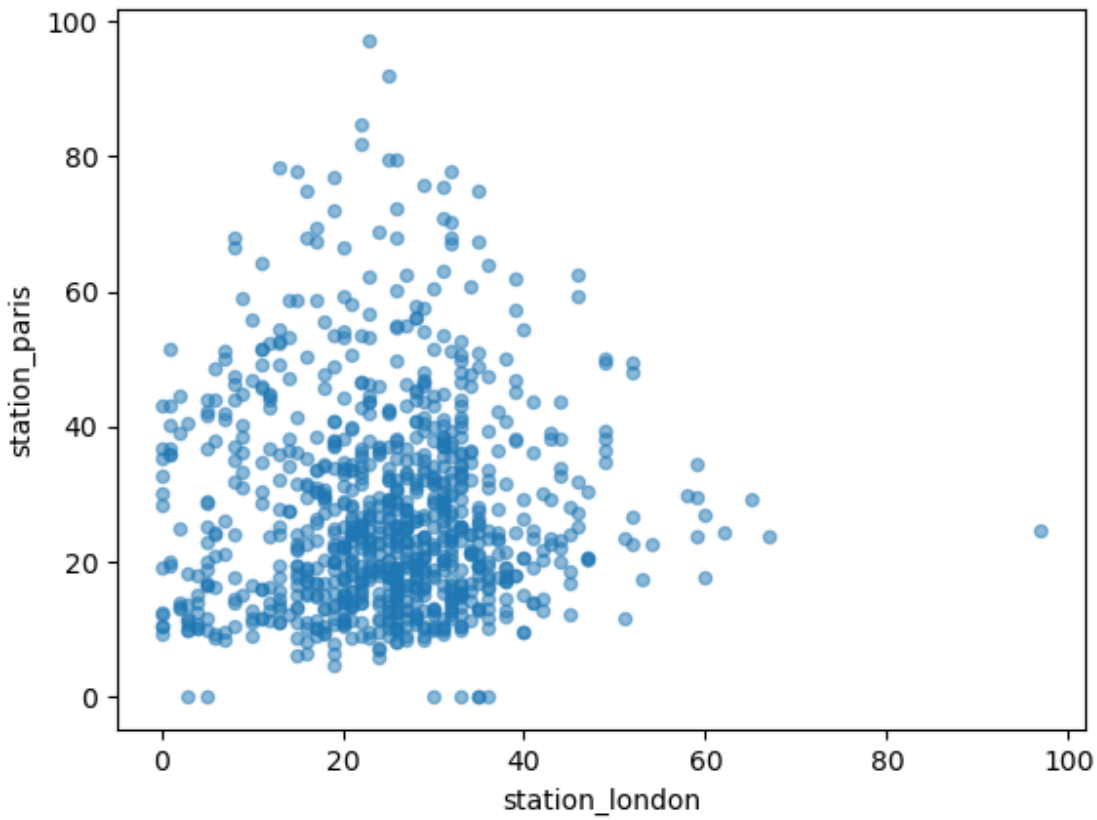
```
In [6]: air_quality["station_paris"].plot()
Out[6]: <AxesSubplot:xlabel='datetime'>
```



To plot a specific column, use the selection method of the *subset data tutorial* in combination with the `plot()` method. Hence, the `plot()` method works on both `Series` and `DataFrame`.

I want to visually compare the $N0_2$ values measured in London versus Paris.

```
In [7]: air_quality.plot.scatter(x="station_london", y="station_paris", alpha=0.5)
Out[7]: <AxesSubplot:xlabel='station_london', ylabel='station_paris'>
```



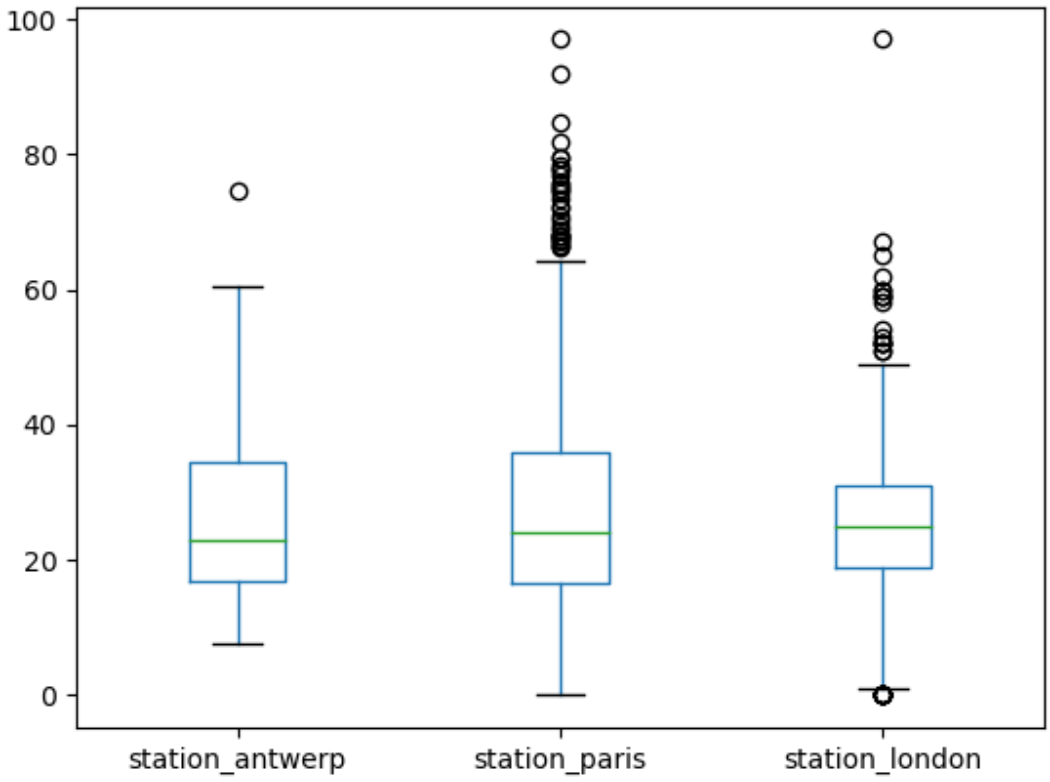
Apart from the default `line` plot when using the `plot` function, a number of alternatives are available to plot data. Let's use some standard Python to get an overview of the available plot methods:

```
In [8]: [
   ...:     method_name
   ...:     for method_name in dir(air_quality.plot)
   ...:     if not method_name.startswith("_")
   ...: ]
   ...:
Out[8]:
['area',
 'bar',
 'barh',
 'box',
 'density',
 'hexbin',
 'hist',
 'kde',
 'line',
 'pie',
 'scatter']
```

Note: In many development environments as well as IPython and Jupyter Notebook, use the TAB button to get an overview of the available methods, for example `air_quality.plot.` + TAB.

One of the options is *DataFrame.plot.box()*, which refers to a boxplot. The `box` method is applicable on the air quality example data:

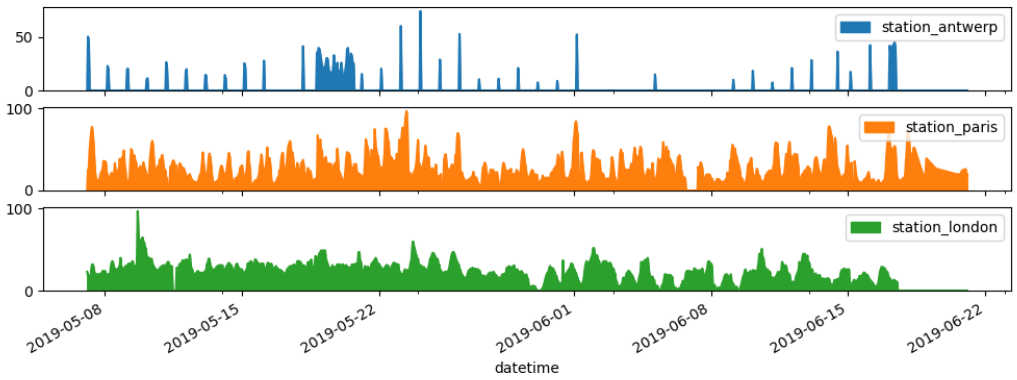
```
In [9]: air_quality.plot.box()
Out[9]: <AxesSubplot:>
```



For an introduction to plots other than the default line plot, see the user guide section about *supported plot styles*.

I want each of the columns in a separate subplot.

```
In [10]: axs = air_quality.plot.area(figsize=(12, 4), subplots=True)
```



Separate subplots for each of the data columns are supported by the `subplots` argument of the `plot` functions. The builtin options available in each of the pandas plot functions that are worthwhile to have a look.

Some more formatting options are explained in the user guide section on *plot formatting*.

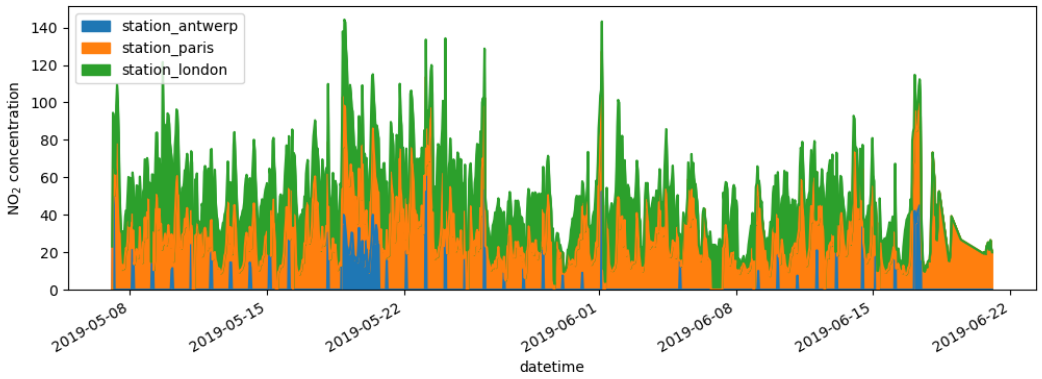
I want to further customize, extend or save the resulting plot.

```
In [11]: fig, axs = plt.subplots(figsize=(12, 4))

In [12]: air_quality.plot.area(ax=axs)
Out[12]: <AxesSubplot:xlabel='datetime'>

In [13]: axs.set_ylabel("NO$_2$ concentration")
Out[13]: Text(0, 0.5, 'NO$_2$ concentration')

In [14]: fig.savefig("no2_concentrations.png")
```



Each of the plot objects created by pandas is a matplotlib object. As Matplotlib provides plenty of options to customize plots, making the link between pandas and Matplotlib explicit enables all the power of matplotlib to the plot. This strategy is applied in the previous example:

```
fig, axs = plt.subplots(figsize=(12, 4))        # Create an empty matplotlib Figure␣
↪and Axes
air_quality.plot.area(ax=axs)                   # Use pandas to put the area plot on␣
↪the prepared Figure/Axes
axs.set_ylabel("NO$_2$ concentration")          # Do any matplotlib customization you␣
↪like
fig.savefig("no2_concentrations.png")           # Save the Figure/Axes using the␣
↪existing matplotlib method.
```

- The `.plot.*` methods are applicable on both Series and DataFrames
- By default, each of the columns is plotted as a different element (line, boxplot,...)
- Any plot created by pandas is a Matplotlib object.

A full overview of plotting in pandas is provided in the *visualization pages*.

```
In [1]: import pandas as pd
```

For this tutorial, air quality data about NO_2 is used, made available by openaq and using the py-openaq package. The `air_quality_no2.csv` data set provides NO_2 values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [2]: air_quality = pd.read_csv("data/air_quality_no2.csv", index_col=0, parse_
↪dates=True)

In [3]: air_quality.head()
Out[3]:
                     station_antwerp  station_paris  station_london
datetime
2019-05-07 02:00:00              NaN            NaN            23.0
2019-05-07 03:00:00             50.5           25.0            19.0
2019-05-07 04:00:00             45.0           27.7            19.0
2019-05-07 05:00:00              NaN           50.4            16.0
2019-05-07 06:00:00              NaN           61.9             NaN
```

How to create new columns derived from existing columns?

I want to express the NO_2 concentration of the station in London in mg/m^3

(*If we assume temperature of 25 degrees Celsius and pressure of 1013 hPa, the conversion factor is 1.882*)

```
In [4]: air_quality["london_mg_per_cubic"] = air_quality["station_london"] * 1.882

In [5]: air_quality.head()
Out[5]:
                     station_antwerp  station_paris  station_london  london_mg_per_
↪cubic
datetime
↪
2019-05-07 02:00:00              NaN            NaN            23.0               43.
↪286
2019-05-07 03:00:00             50.5           25.0            19.0               35.
↪758
2019-05-07 04:00:00             45.0           27.7            19.0               35.
↪758
2019-05-07 05:00:00              NaN           50.4            16.0               30.
↪112
2019-05-07 06:00:00              NaN           61.9             NaN
↪NaN
```

To create a new column, use the `[]` brackets with the new column name at the left side of the assignment.

Note: The calculation of the values is done **element_wise**. This means all values in the given column are multiplied by the value 1.882 at once. You do not need to use a loop to iterate each of the rows!

I want to check the ratio of the values in Paris versus Antwerp and save the result in a new column

```
In [6]: air_quality["ratio_paris_antwerp"] = (
   ...:     air_quality["station_paris"] / air_quality["station_antwerp"]
   ...: )
   ...:

In [7]: air_quality.head()
```

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```
Out[7]:
                     station_antwerp  station_paris  station_london  london_mg_per_
↪cubic  ratio_paris_antwerp
datetime                                                                          ⌊
↪
2019-05-07 02:00:00              NaN            NaN            23.0               43.
↪286                  NaN
2019-05-07 03:00:00             50.5           25.0            19.0               35.
↪758             0.495050
2019-05-07 04:00:00             45.0           27.7            19.0               35.
↪758             0.615556
2019-05-07 05:00:00              NaN           50.4            16.0               30.
↪112                  NaN
2019-05-07 06:00:00              NaN           61.9             NaN                ⌊
↪NaN                  NaN
```

The calculation is again element-wise, so the `/` is applied *for the values in each row*.

Also other mathematical operators (+, -, *, /) or logical operators (<, >, =,...) work element wise. The latter was already used in the *subset data tutorial* to filter rows of a table using a conditional expression.

I want to rename the data columns to the corresponding station identifiers used by openAQ

```
In [8]: air_quality_renamed = air_quality.rename(
   ...:     columns={
   ...:         "station_antwerp": "BETR801",
   ...:         "station_paris": "FR04014",
   ...:         "station_london": "London Westminster",
   ...:     }
   ...: )
   ...:
```

```
In [9]: air_quality_renamed.head()
Out[9]:
                     BETR801  FR04014  London Westminster  london_mg_per_cubic  ratio_
↪paris_antwerp
datetime                                                                          ⌊
↪
2019-05-07 02:00:00      NaN      NaN                23.0                43.286       ⌊
↪          NaN
2019-05-07 03:00:00     50.5     25.0                19.0                35.758       ⌊
↪     0.495050
2019-05-07 04:00:00     45.0     27.7                19.0                35.758       ⌊
↪     0.615556
2019-05-07 05:00:00      NaN     50.4                16.0                30.112       ⌊
↪          NaN
2019-05-07 06:00:00      NaN     61.9                 NaN                   NaN       ⌊
↪          NaN
```

The `rename()` function can be used for both row labels and column labels. Provide a dictionary with the keys the current names and the values the new names to update the corresponding names.

The mapping should not be restricted to fixed names only, but can be a mapping function as well. For example, converting the column names to lowercase letters can be done using a function as well:

```
In [10]: air_quality_renamed = air_quality_renamed.rename(columns=str.lower)
```

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```
In [11]: air_quality_renamed.head()
Out[11]:
                     betr801  fr04014  london westminster  london_mg_per_cubic  ratio_
↪paris_antwerp
datetime                                                                            ␣
↪
2019-05-07 02:00:00      NaN      NaN                23.0                43.286       ␣
↪          NaN
2019-05-07 03:00:00     50.5     25.0                19.0                35.758       ␣
↪     0.495050
2019-05-07 04:00:00     45.0     27.7                19.0                35.758       ␣
↪     0.615556
2019-05-07 05:00:00      NaN     50.4                16.0                30.112       ␣
↪          NaN
2019-05-07 06:00:00      NaN     61.9                 NaN                   NaN       ␣
↪          NaN
```

Details about column or row label renaming is provided in the user guide section on *renaming labels*.

- Create a new column by assigning the output to the DataFrame with a new column name in between the `[]`.
- Operations are element-wise, no need to loop over rows.
- Use `rename` with a dictionary or function to rename row labels or column names.

The user guide contains a separate section on *column addition and deletion*.

```
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")

In [3]: titanic.head()
Out[3]:
   PassengerId  Survived  Pclass                                                Name  .
↪..            Ticket     Fare  Cabin  Embarked
0            1         0       3                            Braund, Mr. Owen Harris  .
↪..         A/5 21171   7.2500    NaN         S
```

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```
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  .
↪..          PC 17599  71.2833    C85         C
2            3         1       3                             Heikkinen, Miss. Laina  .
↪..  STON/O2. 3101282   7.9250    NaN         S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  .
↪..             113803  53.1000   C123         S
4            5         0       3                           Allen, Mr. William Henry  .
↪..             373450   8.0500    NaN         S

[5 rows x 12 columns]
```

How to calculate summary statistics?

Aggregating statistics

What is the average age of the Titanic passengers?

```
In [4]: titanic["Age"].mean()
Out[4]: 29.69911764705882
```

Different statistics are available and can be applied to columns with numerical data. Operations in general exclude missing data and operate across rows by default.

What is the median age and ticket fare price of the Titanic passengers?

```
In [5]: titanic[["Age", "Fare"]].median()
Out[5]:
Age     28.0000
Fare    14.4542
dtype: float64
```

The statistic applied to multiple columns of a `DataFrame` (the selection of two columns return a `DataFrame`, see the *subset data tutorial*) is calculated for each numeric column.

The aggregating statistic can be calculated for multiple columns at the same time. Remember the `describe` function from *first tutorial* tutorial?

```
In [6]: titanic[["Age", "Fare"]].describe()
Out[6]:
              Age        Fare
count  714.000000  891.000000
mean    29.699118   32.204208
std     14.526497   49.693429
min      0.420000    0.000000
25%     20.125000    7.910400
50%     28.000000   14.454200
75%     38.000000   31.000000
max     80.000000  512.329200
```

Instead of the predefined statistics, specific combinations of aggregating statistics for given columns can be defined using the *`DataFrame.agg()`* method:

```
In [7]: titanic.agg(
   ...:     {
   ...:         "Age": ["min", "max", "median", "skew"],
   ...:         "Fare": ["min", "max", "median", "mean"],
   ...:     }
   ...: )
   ...:
Out[7]:
               Age        Fare
min       0.420000    0.000000
max      80.000000  512.329200
median   28.000000   14.454200
skew      0.389108         NaN
mean           NaN   32.204208
```

Details about descriptive statistics are provided in the user guide section on *descriptive statistics*.

Aggregating statistics grouped by category

What is the average age for male versus female Titanic passengers?

```
In [8]: titanic[["Sex", "Age"]].groupby("Sex").mean()
Out[8]:
               Age
Sex
female  27.915709
male    30.726645
```

As our interest is the average age for each gender, a subselection on these two columns is made first: `titanic[["Sex", "Age"]]`. Next, the *`groupby()`* method is applied on the `Sex` column to make a group per category. The average age *for each gender* is calculated and returned.

Calculating a given statistic (e.g. `mean` age) *for each category in a column* (e.g. male/female in the `Sex` column) is a common pattern. The `groupby` method is used to support this type of operations. More general, this fits in the more general `split-apply-combine` pattern:

- **Split** the data into groups
- **Apply** a function to each group independently
- **Combine** the results into a data structure

The apply and combine steps are typically done together in pandas.

In the previous example, we explicitly selected the 2 columns first. If not, the `mean` method is applied to each column containing numerical columns:

```
In [9]: titanic.groupby("Sex").mean()
Out[9]:
        PassengerId  Survived    Pclass        Age     SibSp     Parch       Fare
Sex
female   431.028662  0.742038  2.159236  27.915709  0.694268  0.649682  44.479818
male     454.147314  0.188908  2.389948  30.726645  0.429809  0.235702  25.523893
```

It does not make much sense to get the average value of the `Pclass`. if we are only interested in the average age for each gender, the selection of columns (rectangular brackets `[]` as usual) is supported on the grouped data as well:

```
In [10]: titanic.groupby("Sex")["Age"].mean()
Out[10]:
Sex
female    27.915709
male      30.726645
Name: Age, dtype: float64
```

Note: The `Pclass` column contains numerical data but actually represents 3 categories (or factors) with respectively the labels '1', '2' and '3'. Calculating statistics on these does not make much sense. Therefore, pandas provides a `Categorical` data type to handle this type of data. More information is provided in the user guide *Categorical data* section.

What is the mean ticket fare price for each of the sex and cabin class combinations?

```
In [11]: titanic.groupby(["Sex", "Pclass"])["Fare"].mean()
Out[11]:
Sex     Pclass
female  1         106.125798
        2          21.970121
        3          16.118810
male    1          67.226127
        2          19.741782
        3          12.661633
Name: Fare, dtype: float64
```

Grouping can be done by multiple columns at the same time. Provide the column names as a list to the *groupby()* method.

A full description on the split-apply-combine approach is provided in the user guide section on *groupby operations*.

Count number of records by category

What is the number of passengers in each of the cabin classes?

```
In [12]: titanic["Pclass"].value_counts()
Out[12]:
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

The *value_counts()* method counts the number of records for each category in a column.

The function is a shortcut, as it is actually a groupby operation in combination with counting of the number of records within each group:

```
In [13]: titanic.groupby("Pclass")["Pclass"].count()
Out[13]:
Pclass
1    216
2    184
```

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```
3    491
Name: Pclass, dtype: int64
```

Note: Both `size` and `count` can be used in combination with `groupby`. Whereas `size` includes `NaN` values and just provides the number of rows (size of the table), `count` excludes the missing values. In the `value_counts` method, use the `dropna` argument to include or exclude the `NaN` values.

The user guide has a dedicated section on `value_counts` , see page on *discretization*.

- Aggregation statistics can be calculated on entire columns or rows
- `groupby` provides the power of the *split-apply-combine* pattern
- `value_counts` is a convenient shortcut to count the number of entries in each category of a variable

A full description on the split-apply-combine approach is provided in the user guide pages about *groupby operations*.

```
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")

In [3]: titanic.head()
Out[3]:
   PassengerId  Survived  Pclass                                                Name  .
↪..            Ticket     Fare  Cabin  Embarked
0            1         0       3                            Braund, Mr. Owen Harris  .
↪..         A/5 21171   7.2500    NaN         S
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  .
↪..          PC 17599  71.2833    C85         C
2            3         1       3                             Heikkinen, Miss. Laina  .
↪..  STON/O2. 3101282   7.9250    NaN         S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  .
↪..            113803  53.1000   C123         S
4            5         0       3                           Allen, Mr. William Henry  .
↪..            373450   8.0500    NaN         S
```

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```
[5 rows x 12 columns]
```

This tutorial uses air quality data about NO_2 and Particulate matter less than 2.5 micrometers, made available by openaq and using the py-openaq package. The `air_quality_long.csv` data set provides NO_2 and PM_{25} values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

The air-quality data set has the following columns:

- city: city where the sensor is used, either Paris, Antwerp or London
- country: country where the sensor is used, either FR, BE or GB
- location: the id of the sensor, either *FR04014*, *BETR801* or *London Westminster*
- parameter: the parameter measured by the sensor, either NO_2 or Particulate matter
- value: the measured value
- unit: the unit of the measured parameter, in this case 'µg/m^3'

and the index of the `DataFrame` is `datetime`, the datetime of the measurement.

Note: The air-quality data is provided in a so-called *long format* data representation with each observation on a separate row and each variable a separate column of the data table. The long/narrow format is also known as the tidy data format.

```
In [4]: air_quality = pd.read_csv(
   ...:     "data/air_quality_long.csv", index_col="date.utc", parse_dates=True
   ...: )
   ...:

In [5]: air_quality.head()
Out[5]:
                           city country location parameter  value   unit
date.utc
2019-06-18 06:00:00+00:00  Antwerpen      BE  BETR801      pm25   18.0  µg/m3
2019-06-17 08:00:00+00:00  Antwerpen      BE  BETR801      pm25    6.5  µg/m3
2019-06-17 07:00:00+00:00  Antwerpen      BE  BETR801      pm25   18.5  µg/m3
2019-06-17 06:00:00+00:00  Antwerpen      BE  BETR801      pm25   16.0  µg/m3
2019-06-17 05:00:00+00:00  Antwerpen      BE  BETR801      pm25    7.5  µg/m3
```

How to reshape the layout of tables?

Sort table rows

I want to sort the Titanic data according to the age of the passengers.

```
In [6]: titanic.sort_values(by="Age").head()
Out[6]:
     PassengerId  Survived  Pclass                                 Name     Sex  ... ␣
↪Parch  Ticket     Fare Cabin  Embarked
803          804         1       3  Thomas, Master. Assad Alexander    male  ...     ␣
↪1    2625   8.5167   NaN         C
755          756         1       2        Hamalainen, Master. Viljo    male  ...     ␣
↪1  250649  14.5000   NaN         S
```

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```
644          645         1       3           Baclini, Miss. Eugenie  female  ...
↪1    2666  19.2583   NaN         C
469          470         1       3    Baclini, Miss. Helene Barbara  female  ...
↪1    2666  19.2583   NaN         C
78            79         1       2    Caldwell, Master. Alden Gates    male  ...
↪2  248738  29.0000   NaN         S

[5 rows x 12 columns]
```

I want to sort the Titanic data according to the cabin class and age in descending order.

```
In [7]: titanic.sort_values(by=['Pclass', 'Age'], ascending=False).head()
Out[7]:
     PassengerId  Survived  Pclass                      Name     Sex   Age  SibSp
↪Parch  Ticket     Fare Cabin Embarked
851          852         0       3        Svensson, Mr. Johan    male  74.0      0
↪   0  347060   7.7750   NaN        S
116          117         0       3       Connors, Mr. Patrick    male  70.5      0
↪   0  370369   7.7500   NaN        Q
280          281         0       3           Duane, Mr. Frank    male  65.0      0
↪   0  336439   7.7500   NaN        Q
483          484         1       3     Turkula, Mrs. (Hedwig)  female  63.0      0
↪   0    4134   9.5875   NaN        S
326          327         0       3  Nysveen, Mr. Johan Hansen    male  61.0      0
↪   0  345364   6.2375   NaN        S
```

With *`Series.sort_values()`*, the rows in the table are sorted according to the defined column(s). The index will follow the row order.

More details about sorting of tables is provided in the using guide section on *sorting data*.

Long to wide table format

Let's use a small subset of the air quality data set. We focus on NO_2 data and only use the first two measurements of each location (i.e. the head of each group). The subset of data will be called `no2_subset`

```
# filter for no2 data only
In [8]: no2 = air_quality[air_quality["parameter"] == "no2"]
```

```
# use 2 measurements (head) for each location (groupby)
In [9]: no2_subset = no2.sort_index().groupby(["location"]).head(2)

In [10]: no2_subset
Out[10]:
                             city country            location parameter  value
↪unit
date.utc
↪
2019-04-09 01:00:00+00:00  Antwerpen      BE             BETR801       no2   22.5  µg/
↪m³
2019-04-09 01:00:00+00:00      Paris      FR             FR04014       no2   24.4  µg/
↪m³
2019-04-09 02:00:00+00:00     London      GB  London Westminster       no2   67.0  µg/
↪m³
2019-04-09 02:00:00+00:00  Antwerpen      BE             BETR801       no2   53.5  µg/
↪m³
```

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```
2019-04-09 02:00:00+00:00      Paris      FR             FR04014       no2   27.4  µg/
↪m³
2019-04-09 03:00:00+00:00     London      GB  London Westminster       no2   67.0  µg/
↪m³
```

I want the values for the three stations as separate columns next to each other

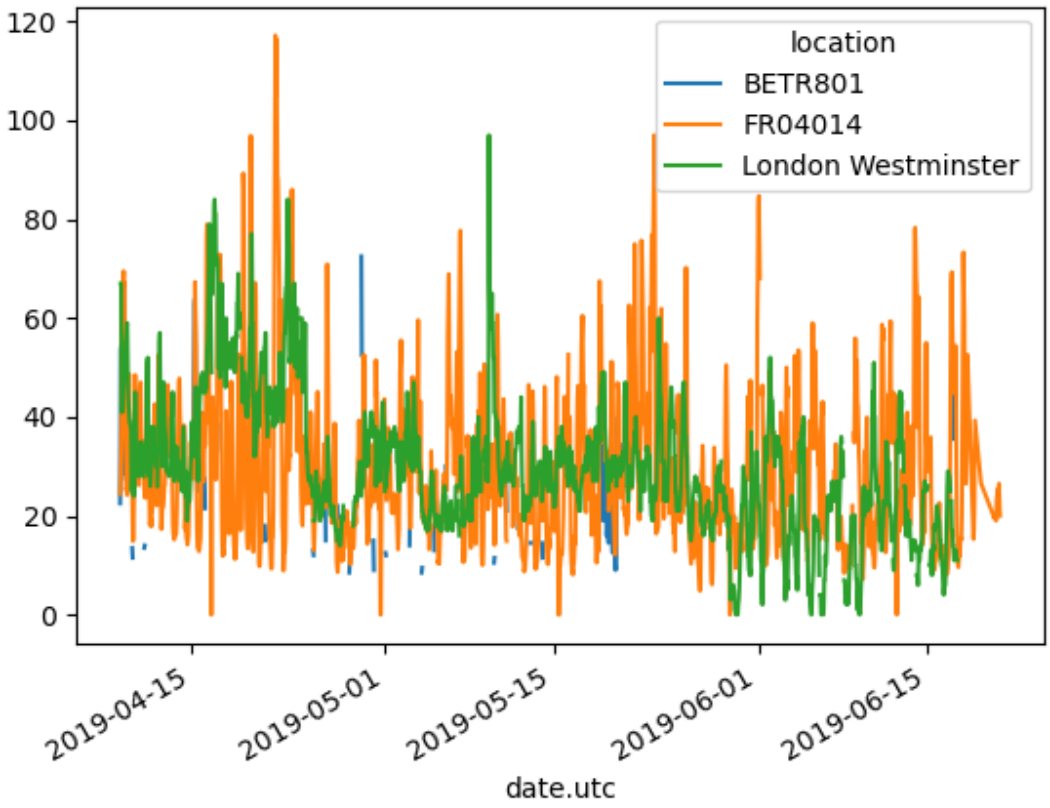
```
In [11]: no2_subset.pivot(columns="location", values="value")
Out[11]:
location                   BETR801  FR04014  London Westminster
date.utc
2019-04-09 01:00:00+00:00     22.5     24.4                 NaN
2019-04-09 02:00:00+00:00     53.5     27.4                67.0
2019-04-09 03:00:00+00:00      NaN      NaN                67.0
```

The *pivot()* function is purely reshaping of the data: a single value for each index/column combination is required.

As pandas support plotting of multiple columns (see *plotting tutorial*) out of the box, the conversion from *long* to *wide* table format enables the plotting of the different time series at the same time:

```
In [12]: no2.head()
Out[12]:
                           city country location parameter  value   unit
date.utc
2019-06-21 00:00:00+00:00  Paris      FR  FR04014       no2   20.0  µg/m³
2019-06-20 23:00:00+00:00  Paris      FR  FR04014       no2   21.8  µg/m³
2019-06-20 22:00:00+00:00  Paris      FR  FR04014       no2   26.5  µg/m³
2019-06-20 21:00:00+00:00  Paris      FR  FR04014       no2   24.9  µg/m³
2019-06-20 20:00:00+00:00  Paris      FR  FR04014       no2   21.4  µg/m³
```

```
In [13]: no2.pivot(columns="location", values="value").plot()
Out[13]: <AxesSubplot:xlabel='date.utc'>
```



Note: When the `index` parameter is not defined, the existing index (row labels) is used.

For more information about `pivot()`, see the user guide section on *pivoting DataFrame objects*.

Pivot table

I want the mean concentrations for NO_2 and $PM_{2.5}$ in each of the stations in table form

```
In [14]: air_quality.pivot_table(
   ....:     values="value", index="location", columns="parameter", aggfunc="mean"
   ....: )
   ....:
Out[14]:
parameter                no2       pm25
location
BETR801            26.950920  23.169492
FR04014            29.374284        NaN
London Westminster 29.740050  13.443568
```

In the case of `pivot()`, the data is only rearranged. When multiple values need to be aggregated (in this specific case, the values on different time steps) `pivot_table()` can be used, providing an aggregation function (e.g. mean)

on how to combine these values.

Pivot table is a well known concept in spreadsheet software. When interested in summary columns for each variable separately as well, put the `margin` parameter to `True`:

```
In [15]: air_quality.pivot_table(
   ....:     values="value",
   ....:     index="location",
   ....:     columns="parameter",
   ....:     aggfunc="mean",
   ....:     margins=True,
   ....: )
   ....:
Out[15]:
parameter                 no2       pm25        All
location
BETR801             26.950920  23.169492  24.982353
FR04014             29.374284        NaN  29.374284
London Westminster  29.740050  13.443568  21.491708
All                 29.430316  14.386849  24.222743
```

For more information about *pivot_table()*, see the user guide section on *pivot tables*.

Note: In case you are wondering, *pivot_table()* is indeed directly linked to *groupby()*. The same result can be derived by grouping on both `parameter` and `location`:

```
air_quality.groupby(["parameter", "location"]).mean()
```

Have a look at *groupby()* in combination with *unstack()* at the user guide section on *combining stats and groupby*.

Wide to long format

Starting again from the wide format table created in the previous section:

```
In [16]: no2_pivoted = no2.pivot(columns="location", values="value").reset_index()

In [17]: no2_pivoted.head()
Out[17]:
location                  date.utc  BETR801  FR04014  London Westminster
0         2019-04-09 01:00:00+00:00     22.5     24.4                 NaN
1         2019-04-09 02:00:00+00:00     53.5     27.4                67.0
2         2019-04-09 03:00:00+00:00     54.5     34.2                67.0
3         2019-04-09 04:00:00+00:00     34.5     48.5                41.0
4         2019-04-09 05:00:00+00:00     46.5     59.5                41.0
```

I want to collect all air quality NO_2 measurements in a single column (long format)

```
In [18]: no_2 = no2_pivoted.melt(id_vars="date.utc")

In [19]: no_2.head()
Out[19]:
                  date.utc location  value
```

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```
0 2019-04-09 01:00:00+00:00  BETR801   22.5
1 2019-04-09 02:00:00+00:00  BETR801   53.5
2 2019-04-09 03:00:00+00:00  BETR801   54.5
3 2019-04-09 04:00:00+00:00  BETR801   34.5
4 2019-04-09 05:00:00+00:00  BETR801   46.5
```

The *pandas.melt()* method on a DataFrame converts the data table from wide format to long format. The column headers become the variable names in a newly created column.

The solution is the short version on how to apply *pandas.melt()*. The method will *melt* all columns NOT mentioned in id_vars together into two columns: A column with the column header names and a column with the values itself. The latter column gets by default the name value.

The *pandas.melt()* method can be defined in more detail:

```
In [20]: no_2 = no2_pivoted.melt(
   ....:     id_vars="date.utc",
   ....:     value_vars=["BETR801", "FR04014", "London Westminster"],
   ....:     value_name="NO_2",
   ....:     var_name="id_location",
   ....: )
   ....:

In [21]: no_2.head()
Out[21]:
                  date.utc id_location  NO_2
0 2019-04-09 01:00:00+00:00     BETR801  22.5
1 2019-04-09 02:00:00+00:00     BETR801  53.5
2 2019-04-09 03:00:00+00:00     BETR801  54.5
3 2019-04-09 04:00:00+00:00     BETR801  34.5
4 2019-04-09 05:00:00+00:00     BETR801  46.5
```

The result in the same, but in more detail defined:

- value_vars defines explicitly which columns to *melt* together
- value_name provides a custom column name for the values column instead of the default column name value
- var_name provides a custom column name for the column collecting the column header names. Otherwise it takes the index name or a default variable

Hence, the arguments value_name and var_name are just user-defined names for the two generated columns. The columns to melt are defined by id_vars and value_vars.

Conversion from wide to long format with *pandas.melt()* is explained in the user guide section on *reshaping by melt*.

- Sorting by one or more columns is supported by sort_values
- The pivot function is purely restructuring of the data, pivot_table supports aggregations
- The reverse of pivot (long to wide format) is melt (wide to long format)

A full overview is available in the user guide on the pages about *reshaping and pivoting*.

```
In [1]: import pandas as pd
```

For this tutorial, air quality data about NO_2 is used, made available by openaq and downloaded using the py-openaq package.

The `air_quality_no2_long.csv` data set provides NO_2 values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [2]: air_quality_no2 = pd.read_csv("data/air_quality_no2_long.csv",
   ...:                               parse_dates=True)
   ...:

In [3]: air_quality_no2 = air_quality_no2[["date.utc", "location",
   ...:                                    "parameter", "value"]]
   ...:

In [4]: air_quality_no2.head()
Out[4]:
                   date.utc location parameter  value
0  2019-06-21 00:00:00+00:00  FR04014       no2   20.0
1  2019-06-20 23:00:00+00:00  FR04014       no2   21.8
2  2019-06-20 22:00:00+00:00  FR04014       no2   26.5
3  2019-06-20 21:00:00+00:00  FR04014       no2   24.9
4  2019-06-20 20:00:00+00:00  FR04014       no2   21.4
```

For this tutorial, air quality data about Particulate matter less than 2.5 micrometers is used, made available by openaq and downloaded using the py-openaq package.

The `air_quality_pm25_long.csv` data set provides PM_{25} values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [5]: air_quality_pm25 = pd.read_csv("data/air_quality_pm25_long.csv",
   ...:                               parse_dates=True)
   ...:

In [6]: air_quality_pm25 = air_quality_pm25[["date.utc", "location",
   ...:                                      "parameter", "value"]]
   ...:

In [7]: air_quality_pm25.head()
Out[7]:
                   date.utc location parameter  value
0  2019-06-18 06:00:00+00:00  BETR801      pm25   18.0
1  2019-06-17 08:00:00+00:00  BETR801      pm25    6.5
2  2019-06-17 07:00:00+00:00  BETR801      pm25   18.5
3  2019-06-17 06:00:00+00:00  BETR801      pm25   16.0
4  2019-06-17 05:00:00+00:00  BETR801      pm25    7.5
```

How to combine data from multiple tables?

Concatenating objects

I want to combine the measurements of NO_2 and PM_{25}, two tables with a similar structure, in a single table

```
In [8]: air_quality = pd.concat([air_quality_pm25, air_quality_no2], axis=0)

In [9]: air_quality.head()
Out[9]:
                   date.utc location parameter  value
```

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```
0  2019-06-18 06:00:00+00:00  BETR801      pm25   18.0
1  2019-06-17 08:00:00+00:00  BETR801      pm25    6.5
2  2019-06-17 07:00:00+00:00  BETR801      pm25   18.5
3  2019-06-17 06:00:00+00:00  BETR801      pm25   16.0
4  2019-06-17 05:00:00+00:00  BETR801      pm25    7.5
```

The *concat()* function performs concatenation operations of multiple tables along one of the axis (row-wise or column-wise).

By default concatenation is along axis 0, so the resulting table combines the rows of the input tables. Let's check the shape of the original and the concatenated tables to verify the operation:

```
In [10]: print('Shape of the ``air_quality_pm25`` table: ', air_quality_pm25.shape)
Shape of the ``air_quality_pm25`` table:  (1110, 4)

In [11]: print('Shape of the ``air_quality_no2`` table: ', air_quality_no2.shape)
Shape of the ``air_quality_no2`` table:  (2068, 4)

In [12]: print('Shape of the resulting ``air_quality`` table: ', air_quality.shape)
Shape of the resulting ``air_quality`` table:  (3178, 4)
```

Hence, the resulting table has 3178 = 1110 + 2068 rows.

Note: The **axis** argument will return in a number of pandas methods that can be applied **along an axis**. A `DataFrame` has two corresponding axes: the first running vertically downwards across rows (axis 0), and the second running horizontally across columns (axis 1). Most operations like concatenation or summary statistics are by default across rows (axis 0), but can be applied across columns as well.

Sorting the table on the datetime information illustrates also the combination of both tables, with the `parameter` column defining the origin of the table (either `no2` from table `air_quality_no2` or `pm25` from table `air_quality_pm25`):

```
In [13]: air_quality = air_quality.sort_values("date.utc")

In [14]: air_quality.head()
Out[14]:
                     date.utc            location parameter  value
2067  2019-05-07 01:00:00+00:00  London Westminster       no2   23.0
1003  2019-05-07 01:00:00+00:00             FR04014       no2   25.0
100   2019-05-07 01:00:00+00:00             BETR801      pm25   12.5
1098  2019-05-07 01:00:00+00:00             BETR801       no2   50.5
1109  2019-05-07 01:00:00+00:00  London Westminster      pm25    8.0
```

In this specific example, the `parameter` column provided by the data ensures that each of the original tables can be identified. This is not always the case. the `concat` function provides a convenient solution with the `keys` argument, adding an additional (hierarchical) row index. For example:

```
In [15]: air_quality_ = pd.concat([air_quality_pm25, air_quality_no2], keys=["PM25",
↪"NO2"])
```

```
In [16]: air_quality_.head()
Out[16]:
                       date.utc location parameter  value
PM25 0  2019-06-18 06:00:00+00:00  BETR801      pm25   18.0
```

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```
     1  2019-06-17 08:00:00+00:00  BETR801      pm25    6.5
     2  2019-06-17 07:00:00+00:00  BETR801      pm25   18.5
     3  2019-06-17 06:00:00+00:00  BETR801      pm25   16.0
     4  2019-06-17 05:00:00+00:00  BETR801      pm25    7.5
```

Note: The existence of multiple row/column indices at the same time has not been mentioned within these tutorials. *Hierarchical indexing* or *MultiIndex* is an advanced and powerful pandas feature to analyze higher dimensional data.

Multi-indexing is out of scope for this pandas introduction. For the moment, remember that the function `reset_index` can be used to convert any level of an index to a column, e.g. `air_quality.reset_index(level=0)`

Feel free to dive into the world of multi-indexing at the user guide section on *advanced indexing*.

More options on table concatenation (row and column wise) and how `concat` can be used to define the logic (union or intersection) of the indexes on the other axes is provided at the section on *object concatenation*.

Join tables using a common identifier

Add the station coordinates, provided by the stations metadata table, to the corresponding rows in the measurements table.

Warning: The air quality measurement station coordinates are stored in a data file `air_quality_stations.csv`, downloaded using the py-openaq package.

```
In [17]: stations_coord = pd.read_csv("data/air_quality_stations.csv")

In [18]: stations_coord.head()
Out[18]:
  location  coordinates.latitude  coordinates.longitude
0  BELAL01              51.23619               4.38522
1  BELHB23              51.17030               4.34100
2  BELLD01              51.10998               5.00486
3  BELLD02              51.12038               5.02155
4  BELR833              51.32766               4.36226
```

Note: The stations used in this example (FR04014, BETR801 and London Westminster) are just three entries enlisted in the metadata table. We only want to add the coordinates of these three to the measurements table, each on the corresponding rows of the `air_quality` table.

```
In [19]: air_quality.head()
Out[19]:
                     date.utc            location parameter  value
2067  2019-05-07 01:00:00+00:00  London Westminster       no2   23.0
1003  2019-05-07 01:00:00+00:00              FR04014       no2   25.0
100   2019-05-07 01:00:00+00:00              BETR801      pm25   12.5
1098  2019-05-07 01:00:00+00:00              BETR801       no2   50.5
1109  2019-05-07 01:00:00+00:00  London Westminster      pm25    8.0
```

```
In [20]: air_quality = pd.merge(air_quality, stations_coord, how="left", on="location
↪")

In [21]: air_quality.head()
Out[21]:
                   date.utc            location parameter  value  coordinates.
↪latitude  coordinates.longitude
0  2019-05-07 01:00:00+00:00  London Westminster       no2   23.0              51.
↪49467               -0.13193
1  2019-05-07 01:00:00+00:00              FR04014       no2   25.0              48.
↪83724                2.39390
2  2019-05-07 01:00:00+00:00              FR04014       no2   25.0              48.
↪83722                2.39390
3  2019-05-07 01:00:00+00:00              BETR801      pm25   12.5              51.
↪20966                4.43182
4  2019-05-07 01:00:00+00:00              BETR801       no2   50.5              51.
↪20966                4.43182
```

Using the *merge()* function, for each of the rows in the `air_quality` table, the corresponding coordinates are added from the `air_quality_stations_coord` table. Both tables have the column `location` in common which is used as a key to combine the information. By choosing the `left` join, only the locations available in the `air_quality` (left) table, i.e. FR04014, BETR801 and London Westminster, end up in the resulting table. The `merge` function supports multiple join options similar to database-style operations.

Add the parameter full description and name, provided by the parameters metadata table, to the measurements table

Warning: The air quality parameters metadata are stored in a data file `air_quality_parameters.csv`, downloaded using the py-openaq package.

```
In [22]: air_quality_parameters = pd.read_csv("data/air_quality_parameters.csv")

In [23]: air_quality_parameters.head()
Out[23]:
     id                                      description  name
0    bc                                   Black Carbon    BC
1    co                                 Carbon Monoxide    CO
2   no2                                Nitrogen Dioxide   NO2
3    o3                                            Ozone    O3
4  pm10  Particulate matter less than 10 micrometers in...  PM10
```

```
In [24]: air_quality = pd.merge(air_quality, air_quality_parameters,
   ....:                       how='left', left_on='parameter', right_on='id')
   ....:

In [25]: air_quality.head()
Out[25]:
                   date.utc            location parameter  ...    id
↪                    description   name
0  2019-05-07 01:00:00+00:00  London Westminster       no2  ...   no2
↪                  Nitrogen Dioxide    NO2
1  2019-05-07 01:00:00+00:00              FR04014       no2  ...   no2
↪                  Nitrogen Dioxide    NO2
2  2019-05-07 01:00:00+00:00              FR04014       no2  ...   no2
↪                  Nitrogen Dioxide    NO2
3  2019-05-07 01:00:00+00:00              BETR801      pm25  ...  pm25  Particulate␣
↪matter less than 2.5 micrometers i...  PM2.5
```

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```
4  2019-05-07 01:00:00+00:00            BETR801       no2  ...    no2
↪                  Nitrogen Dioxide    NO2

[5 rows x 9 columns]
```

Compared to the previous example, there is no common column name. However, the `parameter` column in the `air_quality` table and the `id` column in the `air_quality_parameters_name` both provide the measured variable in a common format. The `left_on` and `right_on` arguments are used here (instead of just `on`) to make the link between the two tables.

pandas supports also inner, outer, and right joins. More information on join/merge of tables is provided in the user guide section on *database style merging of tables*. Or have a look at the *comparison with SQL* page.

- Multiple tables can be concatenated both column-wise and row-wise using the `concat` function.
- For database-like merging/joining of tables, use the `merge` function.

See the user guide for a full description of the various *facilities to combine data tables*.

```
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt
```

For this tutorial, air quality data about NO_2 and Particulate matter less than 2.5 micrometers is used, made available by openaq and downloaded using the py-openaq package. The `air_quality_no2_long.csv"` data set provides NO_2 values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [3]: air_quality = pd.read_csv("data/air_quality_no2_long.csv")

In [4]: air_quality = air_quality.rename(columns={"date.utc": "datetime"})

In [5]: air_quality.head()
Out[5]:
    city country                  datetime location parameter  value   unit
0  Paris      FR  2019-06-21 00:00:00+00:00  FR04014       no2   20.0  µg/m³
1  Paris      FR  2019-06-20 23:00:00+00:00  FR04014       no2   21.8  µg/m³
2  Paris      FR  2019-06-20 22:00:00+00:00  FR04014       no2   26.5  µg/m³
3  Paris      FR  2019-06-20 21:00:00+00:00  FR04014       no2   24.9  µg/m³
4  Paris      FR  2019-06-20 20:00:00+00:00  FR04014       no2   21.4  µg/m³
```

```
In [6]: air_quality.city.unique()
Out[6]: array(['Paris', 'Antwerpen', 'London'], dtype=object)
```

How to handle time series data with ease?

Using pandas datetime properties

I want to work with the dates in the column `datetime` as datetime objects instead of plain text

```
In [7]: air_quality["datetime"] = pd.to_datetime(air_quality["datetime"])

In [8]: air_quality["datetime"]
Out[8]:
0      2019-06-21 00:00:00+00:00
```

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```
1      2019-06-20 23:00:00+00:00
2      2019-06-20 22:00:00+00:00
3      2019-06-20 21:00:00+00:00
4      2019-06-20 20:00:00+00:00
                  ...
2063   2019-05-07 06:00:00+00:00
2064   2019-05-07 04:00:00+00:00
2065   2019-05-07 03:00:00+00:00
2066   2019-05-07 02:00:00+00:00
2067   2019-05-07 01:00:00+00:00
Name: datetime, Length: 2068, dtype: datetime64[ns, UTC]
```

Initially, the values in `datetime` are character strings and do not provide any datetime operations (e.g. extract the year, day of the week,...). By applying the `to_datetime` function, pandas interprets the strings and convert these to datetime (i.e. `datetime64[ns, UTC]`) objects. In pandas we call these datetime objects similar to `datetime.datetime` from the standard library as *`pandas.Timestamp`*.

Note: As many data sets do contain datetime information in one of the columns, pandas input function like *`pandas.read_csv()`* and *`pandas.read_json()`* can do the transformation to dates when reading the data using the `parse_dates` parameter with a list of the columns to read as Timestamp:

```
pd.read_csv("../data/air_quality_no2_long.csv", parse_dates=["datetime"])
```

Why are these *`pandas.Timestamp`* objects useful? Let's illustrate the added value with some example cases.

What is the start and end date of the time series data set we are working with?

```
In [9]: air_quality["datetime"].min(), air_quality["datetime"].max()
Out[9]:
(Timestamp('2019-05-07 01:00:00+0000', tz='UTC'),
 Timestamp('2019-06-21 00:00:00+0000', tz='UTC'))
```

Using *`pandas.Timestamp`* for datetimes enables us to calculate with date information and make them comparable. Hence, we can use this to get the length of our time series:

```
In [10]: air_quality["datetime"].max() - air_quality["datetime"].min()
Out[10]: Timedelta('44 days 23:00:00')
```

The result is a *`pandas.Timedelta`* object, similar to `datetime.timedelta` from the standard Python library and defining a time duration.

The various time concepts supported by pandas are explained in the user guide section on *time related concepts*.

I want to add a new column to the `DataFrame` containing only the month of the measurement

```
In [11]: air_quality["month"] = air_quality["datetime"].dt.month

In [12]: air_quality.head()
Out[12]:
    city country                  datetime location parameter  value   unit  month
0  Paris      FR 2019-06-21 00:00:00+00:00  FR04014       no2   20.0  µg/m³      6
1  Paris      FR 2019-06-20 23:00:00+00:00  FR04014       no2   21.8  µg/m³      6
2  Paris      FR 2019-06-20 22:00:00+00:00  FR04014       no2   26.5  µg/m³      6
3  Paris      FR 2019-06-20 21:00:00+00:00  FR04014       no2   24.9  µg/m³      6
4  Paris      FR 2019-06-20 20:00:00+00:00  FR04014       no2   21.4  µg/m³      6
```

By using `Timestamp` objects for dates, a lot of time-related properties are provided by pandas. For example the `month`, but also `year`, `weekofyear`, `quarter`,... All of these properties are accessible by the `dt` accessor.

An overview of the existing date properties is given in the *time and date components overview table*. More details about the `dt` accessor to return datetime like properties are explained in a dedicated section on the *dt accessor*.

What is the average NO_2 concentration for each day of the week for each of the measurement locations?

```
In [13]: air_quality.groupby(
   ....:     [air_quality["datetime"].dt.weekday, "location"])["value"].mean()
   ....:
Out[13]:
datetime  location
0         BETR801               27.875000
          FR04014               24.856250
          London Westminster    23.969697
1         BETR801               22.214286
          FR04014               30.999359
                                  ...
5         FR04014               25.266154
          London Westminster    24.977612
6         BETR801               21.896552
          FR04014               23.274306
          London Westminster    24.859155
Name: value, Length: 21, dtype: float64
```

Remember the split-apply-combine pattern provided by `groupby` from the *tutorial on statistics calculation*? Here, we want to calculate a given statistic (e.g. mean NO_2) **for each weekday** and **for each measurement location**. To group on weekdays, we use the datetime property `weekday` (with Monday=0 and Sunday=6) of pandas `Timestamp`, which is also accessible by the `dt` accessor. The grouping on both locations and weekdays can be done to split the calculation of the mean on each of these combinations.

Danger: As we are working with a very short time series in these examples, the analysis does not provide a long-term representative result!

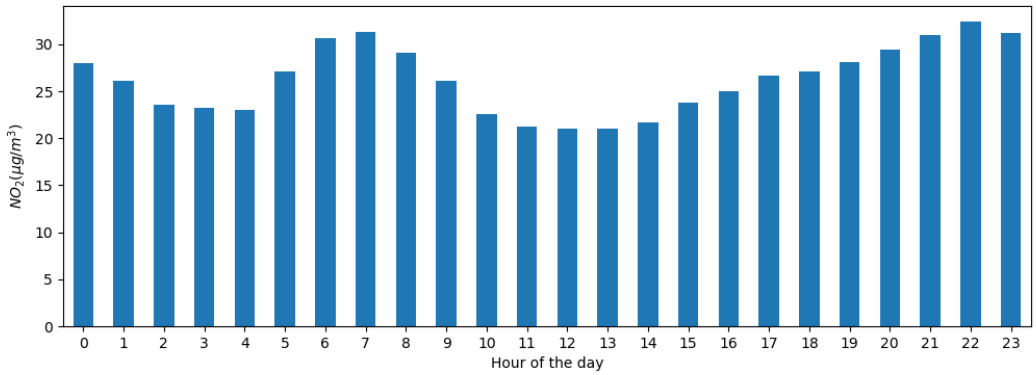
Plot the typical NO_2 pattern during the day of our time series of all stations together. In other words, what is the average value for each hour of the day?

```
In [14]: fig, axs = plt.subplots(figsize=(12, 4))

In [15]: air_quality.groupby(air_quality["datetime"].dt.hour)["value"].mean().plot(
   ....:     kind='bar', rot=0, ax=axs
   ....: )
   ....:
Out[15]: <AxesSubplot:xlabel='datetime'>

In [16]: plt.xlabel("Hour of the day");  # custom x label using matplotlib

In [17]: plt.ylabel("$NO_2 (µg/m^3)$");
```



Similar to the previous case, we want to calculate a given statistic (e.g. mean NO_2) **for each hour of the day** and we can use the split-apply-combine approach again. For this case, we use the datetime property `hour` of pandas `Timestamp`, which is also accessible by the `dt` accessor.

Datetime as index

In the *tutorial on reshaping*, *`pivot()`* was introduced to reshape the data table with each of the measurements locations as a separate column:

```
In [18]: no_2 = air_quality.pivot(index="datetime", columns="location", values="value
↪")

In [19]: no_2.head()
Out[19]:
location                   BETR801  FR04014  London Westminster
datetime
2019-05-07 01:00:00+00:00     50.5     25.0                23.0
2019-05-07 02:00:00+00:00     45.0     27.7                19.0
2019-05-07 03:00:00+00:00      NaN     50.4                19.0
2019-05-07 04:00:00+00:00      NaN     61.9                16.0
2019-05-07 05:00:00+00:00      NaN     72.4                 NaN
```

Note: By pivoting the data, the datetime information became the index of the table. In general, setting a column as an index can be achieved by the `set_index` function.

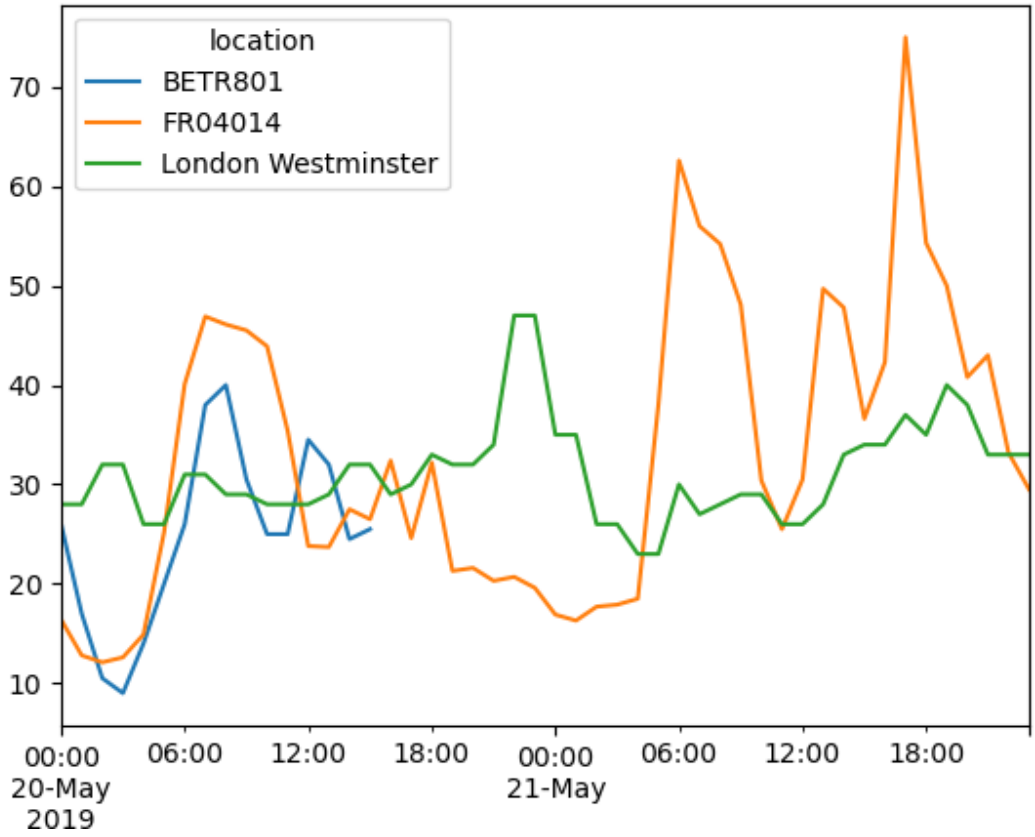
Working with a datetime index (i.e. `DatetimeIndex`) provides powerful functionalities. For example, we do not need the `dt` accessor to get the time series properties, but have these properties available on the index directly:

```
In [20]: no_2.index.year, no_2.index.weekday
Out[20]:
(Int64Index([2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019,
             ...
             2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019],
            dtype='int64', name='datetime', length=1033),
 Int64Index([1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
             ...
             3, 3, 3, 3, 3, 3, 3, 3, 3, 4],
            dtype='int64', name='datetime', length=1033))
```

Some other advantages are the convenient subsetting of time period or the adapted time scale on plots. Let's apply this on our data.

Create a plot of the NO_2 values in the different stations from the 20th of May till the end of 21st of May

```
In [21]: no_2["2019-05-20":"2019-05-21"].plot();
```



By providing a **string that parses to a datetime**, a specific subset of the data can be selected on a `DatetimeIndex`.

More information on the `DatetimeIndex` and the slicing by using strings is provided in the section on *time series indexing*.

Resample a time series to another frequency

Aggregate the current hourly time series values to the monthly maximum value in each of the stations.

```
In [22]: monthly_max = no_2.resample("M").max()

In [23]: monthly_max
Out[23]:
location                   BETR801  FR04014  London Westminster
datetime
2019-05-31 00:00:00+00:00     74.5     97.0                97.0
2019-06-30 00:00:00+00:00     52.5     84.7                52.0
```

A very powerful method on time series data with a datetime index, is the ability to `resample()` time series to another frequency (e.g., converting secondly data into 5-minutely data).

The `resample()` method is similar to a groupby operation:

- it provides a time-based grouping, by using a string (e.g. `M`, `5H`,...) that defines the target frequency
- it requires an aggregation function such as `mean`, `max`,...

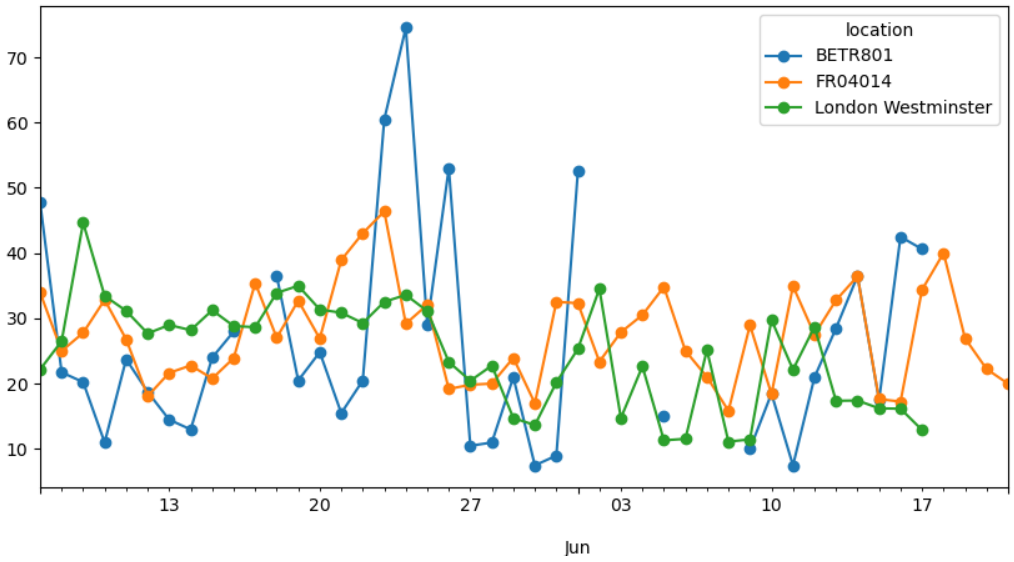
An overview of the aliases used to define time series frequencies is given in the *offset aliases overview table*.

When defined, the frequency of the time series is provided by the `freq` attribute:

```
In [24]: monthly_max.index.freq
Out[24]: <MonthEnd>
```

Make a plot of the daily mean NO_2 value in each of the stations.

```
In [25]: no_2.resample("D").mean().plot(style="-o", figsize=(10, 5));
```



More details on the power of time series `resampling` is provided in the user guide section on *resampling*.

- Valid date strings can be converted to datetime objects using `to_datetime` function or as part of read functions.
- Datetime objects in pandas support calculations, logical operations and convenient date-related properties using the `dt` accessor.
- A `DatetimeIndex` contains these date-related properties and supports convenient slicing.
- `Resample` is a powerful method to change the frequency of a time series.

A full overview on time series is given on the pages on *time series and date functionality*.

```
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.

- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")

In [3]: titanic.head()
Out[3]:
   PassengerId  Survived  Pclass                                                Name  .
↪..             Ticket     Fare  Cabin  Embarked
0            1         0       3                            Braund, Mr. Owen Harris  .
↪..          A/5 21171   7.2500    NaN         S
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  .
↪..           PC 17599  71.2833    C85         C
2            3         1       3                             Heikkinen, Miss. Laina  .
↪..  STON/O2. 3101282   7.9250    NaN         S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  .
↪..             113803  53.1000   C123         S
4            5         0       3                           Allen, Mr. William Henry  .
↪..             373450   8.0500    NaN         S

[5 rows x 12 columns]
```

How to manipulate textual data?

Make all name characters lowercase.

```
In [4]: titanic["Name"].str.lower()
Out[4]:
0                                braund, mr. owen harris
1      cumings, mrs. john bradley (florence briggs th...
2                                heikkinen, miss. laina
3           futrelle, mrs. jacques heath (lily may peel)
4                                allen, mr. william henry
                             ...
886                              montvila, rev. juozas
887                       graham, miss. margaret edith
888           johnston, miss. catherine helen "carrie"
889                              behr, mr. karl howell
890                                dooley, mr. patrick
Name: Name, Length: 891, dtype: object
```

To make each of the strings in the `Name` column lowercase, select the `Name` column (see the *tutorial on selection of data*), add the `str` accessor and apply the `lower` method. As such, each of the strings is converted element-wise.

Similar to datetime objects in the *time series tutorial* having a `dt` accessor, a number of specialized string methods are available when using the `str` accessor. These methods have in general matching names with the equivalent built-in string methods for single elements, but are applied element-wise (remember *element-wise calculations*?) on each of the values of the columns.

Create a new column `Surname` that contains the surname of the passengers by extracting the part before the comma.

```
In [5]: titanic["Name"].str.split(",")
Out[5]:
0                              [Braund,  Mr. Owen Harris]
1      [Cumings,  Mrs. John Bradley (Florence Briggs ...
2                               [Heikkinen,  Miss. Laina]
3        [Futrelle,  Mrs. Jacques Heath (Lily May Peel)]
4                            [Allen,  Mr. William Henry]
                             ...
886                             [Montvila,  Rev. Juozas]
887                      [Graham,  Miss. Margaret Edith]
888          [Johnston,  Miss. Catherine Helen "Carrie"]
889                              [Behr,  Mr. Karl Howell]
890                                [Dooley,  Mr. Patrick]
Name: Name, Length: 891, dtype: object
```

Using the *`Series.str.split()`* method, each of the values is returned as a list of 2 elements. The first element is the part before the comma and the second element is the part after the comma.

```
In [6]: titanic["Surname"] = titanic["Name"].str.split(",").str.get(0)

In [7]: titanic["Surname"]
Out[7]:
0         Braund
1        Cumings
2      Heikkinen
3       Futrelle
4          Allen
          ...
886     Montvila
887       Graham
888     Johnston
889         Behr
890       Dooley
Name: Surname, Length: 891, dtype: object
```

As we are only interested in the first part representing the surname (element 0), we can again use the `str` accessor and apply *`Series.str.get()`* to extract the relevant part. Indeed, these string functions can be concatenated to combine multiple functions at once!

More information on extracting parts of strings is available in the user guide section on *splitting and replacing strings*.

Extract the passenger data about the countesses on board of the Titanic.

```
In [8]: titanic["Name"].str.contains("Countess")
Out[8]:
0      False
1      False
2      False
3      False
4      False
       ...
```

(continues on next page)

(continued from previous page)

```
886    False
887    False
888    False
889    False
890    False
Name: Name, Length: 891, dtype: bool
```

```
In [9]: titanic[titanic["Name"].str.contains("Countess")]
Out[9]:
     PassengerId  Survived  Pclass                                                Name␣
↪ ...  Fare  Cabin  Embarked  Surname
759          760         1       1  Rothes, the Countess. of (Lucy Noel Martha Dye...␣
↪ ...  86.5    B77         S   Rothes

[1 rows x 13 columns]
```

(*Interested in her story? See* Wikipedia*!*)

The string method *`Series.str.contains()`* checks for each of the values in the column `Name` if the string contains the word `Countess` and returns for each of the values `True` (`Countess` is part of the name) or `False` (`Countess` is not part of the name). This output can be used to subselect the data using conditional (boolean) indexing introduced in the *subsetting of data tutorial*. As there was only one countess on the Titanic, we get one row as a result.

Note: More powerful extractions on strings are supported, as the *`Series.str.contains()`* and *`Series.str.extract()`* methods accept regular expressions, but out of scope of this tutorial.

More information on extracting parts of strings is available in the user guide section on *string matching and extracting*.

Which passenger of the Titanic has the longest name?

```
In [10]: titanic["Name"].str.len()
Out[10]:
0      23
1      51
2      22
3      44
4      24
       ..
886    21
887    28
888    40
889    21
890    19
Name: Name, Length: 891, dtype: int64
```

To get the longest name we first have to get the lengths of each of the names in the `Name` column. By using pandas string methods, the *`Series.str.len()`* function is applied to each of the names individually (element-wise).

```
In [11]: titanic["Name"].str.len().idxmax()
Out[11]: 307
```

Next, we need to get the corresponding location, preferably the index label, in the table for which the name length is the largest. The *`idxmax()`* method does exactly that. It is not a string method and is applied to integers, so no `str` is used.

```
In [12]: titanic.loc[titanic["Name"].str.len().idxmax(), "Name"]
Out[12]: 'Penasco y Castellana, Mrs. Victor de Satode (Maria Josefa Perez de Soto y␣
↪Vallejo)'
```

Based on the index name of the row (`307`) and the column (`Name`), we can do a selection using the `loc` operator, introduced in the tutorial on subsetting.

In the "Sex" column, replace values of "male" by "M" and values of "female" by "F".

```
In [13]: titanic["Sex_short"] = titanic["Sex"].replace({"male": "M", "female": "F"})

In [14]: titanic["Sex_short"]
Out[14]:
0      M
1      F
2      F
3      F
4      M
      ..
886    M
887    F
888    F
889    M
890    M
Name: Sex_short, Length: 891, dtype: object
```

Whereas *`replace()`* is not a string method, it provides a convenient way to use mappings or vocabularies to translate certain values. It requires a `dictionary` to define the mapping `{from : to}`.

Warning: There is also a *`replace()`* method available to replace a specific set of characters. However, when having a mapping of multiple values, this would become:

```
titanic["Sex_short"] = titanic["Sex"].str.replace("female", "F")
titanic["Sex_short"] = titanic["Sex_short"].str.replace("male", "M")
```

This would become cumbersome and easily lead to mistakes. Just think (or try out yourself) what would happen if those two statements are applied in the opposite order...

- String methods are available using the `str` accessor.
- String methods work element-wise and can be used for conditional indexing.
- The `replace` method is a convenient method to convert values according to a given dictionary.

A full overview is provided in the user guide pages on *working with text data*.

1.4.4 Comparison with other tools

Comparison with R / R libraries

Since pandas aims to provide a lot of the data manipulation and analysis functionality that people use R for, this page was started to provide a more detailed look at the R language and its many third party libraries as they relate to pandas. In comparisons with R and CRAN libraries, we care about the following things:

- **Functionality / flexibility**: what can/cannot be done with each tool
- **Performance**: how fast are operations. Hard numbers/benchmarks are preferable

- **Ease-of-use**: Is one tool easier/harder to use (you may have to be the judge of this, given side-by-side code comparisons)

This page is also here to offer a bit of a translation guide for users of these R packages.

For transfer of `DataFrame` objects from pandas to R, one option is to use HDF5 files, see *External compatibility* for an example.

Quick reference

We'll start off with a quick reference guide pairing some common R operations using dplyr with pandas equivalents.

Querying, filtering, sampling

R	pandas
`dim(df)`	`df.shape`
`head(df)`	`df.head()`
`slice(df, 1:10)`	`df.iloc[:9]`
`filter(df, col1 == 1, col2 == 1)`	`df.query('col1 == 1 & col2 == 1')`
`df[df$col1 == 1 & df$col2 == 1,]`	`df[(df.col1 == 1) & (df.col2 == 1)]`
`select(df, col1, col2)`	`df[['col1', 'col2']]`
`select(df, col1:col3)`	`df.loc[:, 'col1':'col3']`
`select(df, -(col1:col3))`	`df.drop(cols_to_drop, axis=1)` but see[1]
`distinct(select(df, col1))`	`df[['col1']].drop_duplicates()`
`distinct(select(df, col1, col2))`	`df[['col1', 'col2']].drop_duplicates()`
`sample_n(df, 10)`	`df.sample(n=10)`
`sample_frac(df, 0.01)`	`df.sample(frac=0.01)`

Sorting

R	pandas
`arrange(df, col1, col2)`	`df.sort_values(['col1', 'col2'])`
`arrange(df, desc(col1))`	`df.sort_values('col1', ascending=False)`

Transforming

R	pandas
`select(df, col_one = col1)`	`df.rename(columns={'col1': 'col_one'})['col_one']`
`rename(df, col_one = col1)`	`df.rename(columns={'col1': 'col_one'})`
`mutate(df, c=a-b)`	`df.assign(c=df['a']-df['b'])`

[1] R's shorthand for a subrange of columns (`select(df, col1:col3)`) can be approached cleanly in pandas, if you have the list of columns, for example `df[cols[1:3]]` or `df.drop(cols[1:3])`, but doing this by column name is a bit messy.

Grouping and summarizing

R	pandas
`summary(df)`	`df.describe()`
`gdf <- group_by(df, col1)`	`gdf = df.groupby('col1')`
`summarise(gdf, avg=mean(col1, na.rm=TRUE))`	`df.groupby('col1').agg({'col1': 'mean'})`
`summarise(gdf, total=sum(col1))`	`df.groupby('col1').sum()`

Base R

Slicing with R's `c`

R makes it easy to access `data.frame` columns by name

```
df <- data.frame(a=rnorm(5), b=rnorm(5), c=rnorm(5), d=rnorm(5), e=rnorm(5))
df[, c("a", "c", "e")]
```

or by integer location

```
df <- data.frame(matrix(rnorm(1000), ncol=100))
df[, c(1:10, 25:30, 40, 50:100)]
```

Selecting multiple columns by name in pandas is straightforward

```
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=list("abc"))

In [2]: df[["a", "c"]]
Out[2]:
          a         c
0  0.469112 -1.509059
1 -1.135632 -0.173215
2  0.119209 -0.861849
3 -2.104569  1.071804
4  0.721555 -1.039575
5  0.271860  0.567020
6  0.276232 -0.673690
7  0.113648  0.524988
8  0.404705 -1.715002
9 -1.039268 -1.157892

In [3]: df.loc[:, ["a", "c"]]
Out[3]:
          a         c
0  0.469112 -1.509059
1 -1.135632 -0.173215
2  0.119209 -0.861849
3 -2.104569  1.071804
4  0.721555 -1.039575
5  0.271860  0.567020
6  0.276232 -0.673690
7  0.113648  0.524988
8  0.404705 -1.715002
9 -1.039268 -1.157892
```

Selecting multiple noncontiguous columns by integer location can be achieved with a combination of the `iloc` indexer attribute and `numpy.r_`.

```
In [4]: named = list("abcdefg")

In [5]: n = 30

In [6]: columns = named + np.arange(len(named), n).tolist()

In [7]: df = pd.DataFrame(np.random.randn(n, n), columns=columns)

In [8]: df.iloc[:, np.r_[:10, 24:30]]
Out[8]:
           a         b         c         d         e         f  ...        24
↪25        26        27        28        29
0  -1.344312  0.844885  1.075770 -0.109050  1.643563 -1.469388  ... -1.170299 -0.
↪226169  0.410835  0.813850  0.132003 -0.827317
1  -0.076467 -1.187678  1.130127 -1.436737 -1.413681  1.607920  ...  0.959726 -1.
↪110336 -0.619976  0.149748 -0.732339  0.687738
2   0.176444  0.403310 -0.154951  0.301624 -2.179861 -1.369849  ...  0.084844  0.
↪432390  1.519970 -0.493662  0.600178  0.274230
3   0.132885 -0.023688  2.410179  1.450520  0.206053 -0.251905  ... -2.484478 -0.
↪281461  0.030711  0.109121  1.126203 -0.977349
4   1.474071 -0.064034 -1.282782  0.781836 -1.071357  0.441153  ... -1.197071 -1.
↪066969 -0.303421 -0.858447  0.306996 -0.028665
..       ...       ...       ...       ...       ...       ...  ...       ...       ..
↪.       ...       ...       ...       ...
25  1.492125 -0.068190  0.681456  1.221829 -0.434352  1.204815  ...  1.944517  0.
↪042344 -0.307904  0.428572  0.880609  0.487645
26  0.725238  0.624607 -0.141185 -0.143948 -0.328162  2.095086  ... -0.846188  1.
↪190624  0.778507  1.008500  1.424017  0.717110
27  1.262419  1.950057  0.301038 -0.933858  0.814946  0.181439  ... -1.341814  0.
↪334281 -0.162227  1.007824  2.826008  1.458383
28 -1.585746 -0.899734  0.921494 -0.211762 -0.059182  0.058308  ...  0.403620 -0.
↪026602 -0.240481  0.577223 -1.088417  0.326687
29 -0.986248  0.169729 -1.158091  1.019673  0.646039  0.917399  ... -1.209247 -0.
↪671466  0.332872 -2.013086 -1.602549  0.333109

[30 rows x 16 columns]
```

aggregate

In R you may want to split data into subsets and compute the mean for each. Using a data.frame called `df` and splitting it into groups `by1` and `by2`:

```
df <- data.frame(
  v1 = c(1,3,5,7,8,3,5,NA,4,5,7,9),
  v2 = c(11,33,55,77,88,33,55,NA,44,55,77,99),
  by1 = c("red", "blue", 1, 2, NA, "big", 1, 2, "red", 1, NA, 12),
  by2 = c("wet", "dry", 99, 95, NA, "damp", 95, 99, "red", 99, NA, NA))
aggregate(x=df[, c("v1", "v2")], by=list(mydf2$by1, mydf2$by2), FUN = mean)
```

The *`groupby()`* method is similar to base R `aggregate` function.

```
In [9]: df = pd.DataFrame(
   ...:     {
```

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```
   ...:          "v1": [1, 3, 5, 7, 8, 3, 5, np.nan, 4, 5, 7, 9],
   ...:          "v2": [11, 33, 55, 77, 88, 33, 55, np.nan, 44, 55, 77, 99],
   ...:          "by1": ["red", "blue", 1, 2, np.nan, "big", 1, 2, "red", 1, np.nan,␣
↪12],
   ...:          "by2": [
   ...:              "wet",
   ...:              "dry",
   ...:              99,
   ...:              95,
   ...:              np.nan,
   ...:              "damp",
   ...:              95,
   ...:              99,
   ...:              "red",
   ...:              99,
   ...:              np.nan,
   ...:              np.nan,
   ...:          ],
   ...:      }
   ...: )
   ...:

In [10]: g = df.groupby(["by1", "by2"])

In [11]: g[["v1", "v2"]].mean()
Out[11]:
            v1    v2
by1  by2
1    95    5.0  55.0
     99    5.0  55.0
2    95    7.0  77.0
     99    NaN   NaN
big  damp  3.0  33.0
blue dry   3.0  33.0
red  red   4.0  44.0
     wet   1.0  11.0
```

For more details and examples see *the groupby documentation*.

match / %in%

A common way to select data in R is using `%in%` which is defined using the function `match`. The operator `%in%` is used to return a logical vector indicating if there is a match or not:

```
s <- 0:4
s %in% c(2,4)
```

The *`isin()`* method is similar to R `%in%` operator:

```
In [12]: s = pd.Series(np.arange(5), dtype=np.float32)

In [13]: s.isin([2, 4])
Out[13]:
0    False
1    False
```

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```
2     True
3    False
4     True
dtype: bool
```

The `match` function returns a vector of the positions of matches of its first argument in its second:

```
s <- 0:4
match(s, c(2,4))
```

For more details and examples see *the reshaping documentation*.

tapply

`tapply` is similar to `aggregate`, but data can be in a ragged array, since the subclass sizes are possibly irregular. Using a data.frame called `baseball`, and retrieving information based on the array `team`:

```
baseball <-
  data.frame(team = gl(5, 5,
             labels = paste("Team", LETTERS[1:5])),
             player = sample(letters, 25),
             batting.average = runif(25, .200, .400))

tapply(baseball$batting.average, baseball.example$team,
       max)
```

In pandas we may use *pivot_table()* method to handle this:

```
In [14]: import random

In [15]: import string

In [16]: baseball = pd.DataFrame(
   ....:     {
   ....:         "team": ["team %d" % (x + 1) for x in range(5)] * 5,
   ....:         "player": random.sample(list(string.ascii_lowercase), 25),
   ....:         "batting avg": np.random.uniform(0.200, 0.400, 25),
   ....:     }
   ....: )
   ....:

In [17]: baseball.pivot_table(values="batting avg", columns="team", aggfunc=np.max)
Out[17]:
team           team 1    team 2    team 3    team 4    team 5
batting avg  0.352134  0.295327  0.397191  0.394457  0.396194
```

For more details and examples see *the reshaping documentation*.

subset

The *query()* method is similar to the base R `subset` function. In R you might want to get the rows of a `data.frame` where one column's values are less than another column's values:

```
df <- data.frame(a=rnorm(10), b=rnorm(10))
subset(df, a <= b)
df[df$a <= df$b,]  # note the comma
```

In pandas, there are a few ways to perform subsetting. You can use *query()* or pass an expression as if it were an index/slice as well as standard boolean indexing:

```
In [18]: df = pd.DataFrame({"a": np.random.randn(10), "b": np.random.randn(10)})

In [19]: df.query("a <= b")
Out[19]:
          a         b
1  0.174950  0.552887
2 -0.023167  0.148084
3 -0.495291 -0.300218
4 -0.860736  0.197378
5 -1.134146  1.720780
7 -0.290098  0.083515
8  0.238636  0.946550

In [20]: df[df["a"] <= df["b"]]
Out[20]:
          a         b
1  0.174950  0.552887
2 -0.023167  0.148084
3 -0.495291 -0.300218
4 -0.860736  0.197378
5 -1.134146  1.720780
7 -0.290098  0.083515
8  0.238636  0.946550

In [21]: df.loc[df["a"] <= df["b"]]
Out[21]:
          a         b
1  0.174950  0.552887
2 -0.023167  0.148084
3 -0.495291 -0.300218
4 -0.860736  0.197378
5 -1.134146  1.720780
7 -0.290098  0.083515
8  0.238636  0.946550
```

For more details and examples see *the query documentation*.

with

An expression using a data.frame called `df` in R with the columns `a` and `b` would be evaluated using `with` like so:

```
df <- data.frame(a=rnorm(10), b=rnorm(10))
with(df, a + b)
df$a + df$b  # same as the previous expression
```

In pandas the equivalent expression, using the *`eval()`* method, would be:

```
In [22]: df = pd.DataFrame({"a": np.random.randn(10), "b": np.random.randn(10)})

In [23]: df.eval("a + b")
Out[23]:
0   -0.091430
1   -2.483890
2   -0.252728
3   -0.626444
4   -0.261740
5    2.149503
6   -0.332214
7    0.799331
8   -2.377245
9    2.104677
dtype: float64

In [24]: df["a"] + df["b"]  # same as the previous expression
Out[24]:
0   -0.091430
1   -2.483890
2   -0.252728
3   -0.626444
4   -0.261740
5    2.149503
6   -0.332214
7    0.799331
8   -2.377245
9    2.104677
dtype: float64
```

In certain cases *`eval()`* will be much faster than evaluation in pure Python. For more details and examples see *the eval documentation*.

plyr

`plyr` is an R library for the split-apply-combine strategy for data analysis. The functions revolve around three data structures in R, `a` for `arrays`, `l` for `lists`, and `d` for `data.frame`. The table below shows how these data structures could be mapped in Python.

R	Python
array	list
lists	dictionary or list of objects
data.frame	dataframe

ddply

An expression using a data.frame called `df` in R where you want to summarize `x` by `month`:

```
require(plyr)
df <- data.frame(
  x = runif(120, 1, 168),
  y = runif(120, 7, 334),
  z = runif(120, 1.7, 20.7),
  month = rep(c(5,6,7,8),30),
  week = sample(1:4, 120, TRUE)
)

ddply(df, .(month, week), summarize,
      mean = round(mean(x), 2),
      sd = round(sd(x), 2))
```

In pandas the equivalent expression, using the *`groupby()`* method, would be:

```
In [25]: df = pd.DataFrame(
   ....:     {
   ....:         "x": np.random.uniform(1.0, 168.0, 120),
   ....:         "y": np.random.uniform(7.0, 334.0, 120),
   ....:         "z": np.random.uniform(1.7, 20.7, 120),
   ....:         "month": [5, 6, 7, 8] * 30,
   ....:         "week": np.random.randint(1, 4, 120),
   ....:     }
   ....: )
   ....:

In [26]: grouped = df.groupby(["month", "week"])

In [27]: grouped["x"].agg([np.mean, np.std])
Out[27]:
                mean        std
month week
5     1      63.653367  40.601965
      2      78.126605  53.342400
      3      92.091886  57.630110
6     1      81.747070  54.339218
      2      70.971205  54.687287
      3     100.968344  54.010081
7     1      61.576332  38.844274
      2      61.733510  48.209013
      3      71.688795  37.595638
8     1      62.741922  34.618153
      2      91.774627  49.790202
      3      73.936856  60.773900
```

For more details and examples see *the groupby documentation*.

reshape / reshape2

melt.array

An expression using a 3 dimensional array called `a` in R where you want to melt it into a data.frame:

```
a <- array(c(1:23, NA), c(2,3,4))
data.frame(melt(a))
```

In Python, since `a` is a list, you can simply use list comprehension.

```
In [28]: a = np.array(list(range(1, 24)) + [np.NAN]).reshape(2, 3, 4)

In [29]: pd.DataFrame([tuple(list(x) + [val]) for x, val in np.ndenumerate(a)])
Out[29]:
    0  1  2     3
0   0  0  0   1.0
1   0  0  1   2.0
2   0  0  2   3.0
3   0  0  3   4.0
4   0  1  0   5.0
..  .. .. ..   ...
19  1  1  3  20.0
20  1  2  0  21.0
21  1  2  1  22.0
22  1  2  2  23.0
23  1  2  3   NaN

[24 rows x 4 columns]
```

melt.list

An expression using a list called `a` in R where you want to melt it into a data.frame:

```
a <- as.list(c(1:4, NA))
data.frame(melt(a))
```

In Python, this list would be a list of tuples, so *`DataFrame()`* method would convert it to a dataframe as required.

```
In [30]: a = list(enumerate(list(range(1, 5)) + [np.NAN]))

In [31]: pd.DataFrame(a)
Out[31]:
   0    1
0  0  1.0
1  1  2.0
2  2  3.0
3  3  4.0
4  4  NaN
```

For more details and examples see *the Into to Data Structures documentation*.

melt.data.frame

An expression using a data.frame called `cheese` in R where you want to reshape the data.frame:

```
cheese <- data.frame(
  first = c('John', 'Mary'),
  last = c('Doe', 'Bo'),
  height = c(5.5, 6.0),
  weight = c(130, 150)
)
melt(cheese, id=c("first", "last"))
```

In Python, the *`melt()`* method is the R equivalent:

```
In [32]: cheese = pd.DataFrame(
   ....:     {
   ....:         "first": ["John", "Mary"],
   ....:         "last": ["Doe", "Bo"],
   ....:         "height": [5.5, 6.0],
   ....:         "weight": [130, 150],
   ....:     }
   ....: )
   ....:

In [33]: pd.melt(cheese, id_vars=["first", "last"])
Out[33]:
  first last variable  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0

In [34]: cheese.set_index(["first", "last"]).stack()  # alternative way
Out[34]:
first  last
John   Doe   height      5.5
             weight    130.0
Mary   Bo    height      6.0
             weight    150.0
dtype: float64
```

For more details and examples see *the reshaping documentation*.

cast

In R `acast` is an expression using a data.frame called `df` in R to cast into a higher dimensional array:

```
df <- data.frame(
  x = runif(12, 1, 168),
  y = runif(12, 7, 334),
  z = runif(12, 1.7, 20.7),
  month = rep(c(5,6,7),4),
  week = rep(c(1,2), 6)
)
```

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```
mdf <- melt(df, id=c("month", "week"))
acast(mdf, week ~ month ~ variable, mean)
```

In Python the best way is to make use of *pivot_table()*:

```
In [35]: df = pd.DataFrame(
   ....:     {
   ....:         "x": np.random.uniform(1.0, 168.0, 12),
   ....:         "y": np.random.uniform(7.0, 334.0, 12),
   ....:         "z": np.random.uniform(1.7, 20.7, 12),
   ....:         "month": [5, 6, 7] * 4,
   ....:         "week": [1, 2] * 6,
   ....:     }
   ....: )
   ....:

In [36]: mdf = pd.melt(df, id_vars=["month", "week"])

In [37]: pd.pivot_table(
   ....:     mdf,
   ....:     values="value",
   ....:     index=["variable", "week"],
   ....:     columns=["month"],
   ....:     aggfunc=np.mean,
   ....: )
   ....:
Out[37]:
month                    5           6           7
variable week
x        1      93.888747   98.762034   55.219673
         2      94.391427   38.112932   83.942781
y        1      94.306912  279.454811  227.840449
         2      87.392662  193.028166  173.899260
z        1      11.016009   10.079307   16.170549
         2       8.476111   17.638509   19.003494
```

Similarly for `dcast` which uses a data.frame called `df` in R to aggregate information based on `Animal` and `FeedType`:

```
df <- data.frame(
  Animal = c('Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
             'Animal2', 'Animal3'),
  FeedType = c('A', 'B', 'A', 'A', 'B', 'B', 'A'),
  Amount = c(10, 7, 4, 2, 5, 6, 2)
)

dcast(df, Animal ~ FeedType, sum, fill=NaN)
# Alternative method using base R
with(df, tapply(Amount, list(Animal, FeedType), sum))
```

Python can approach this in two different ways. Firstly, similar to above using *pivot_table()*:

```
In [38]: df = pd.DataFrame(
   ....:     {
   ....:         "Animal": [
   ....:             "Animal1",
```

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```
   ....:                 "Animal2",
   ....:                 "Animal3",
   ....:                 "Animal2",
   ....:                 "Animal1",
   ....:                 "Animal2",
   ....:                 "Animal3",
   ....:             ],
   ....:             "FeedType": ["A", "B", "A", "A", "B", "B", "A"],
   ....:             "Amount": [10, 7, 4, 2, 5, 6, 2],
   ....:         }
   ....: )
   ....:

In [39]: df.pivot_table(values="Amount", index="Animal", columns="FeedType", aggfunc=
↪"sum")
Out[39]:
FeedType     A     B
Animal
Animal1   10.0   5.0
Animal2    2.0  13.0
Animal3    6.0   NaN
```

The second approach is to use the *groupby()* method:

```
In [40]: df.groupby(["Animal", "FeedType"])["Amount"].sum()
Out[40]:
Animal   FeedType
Animal1  A           10
         B            5
Animal2  A            2
         B           13
Animal3  A            6
Name: Amount, dtype: int64
```

For more details and examples see *the reshaping documentation* or *the groupby documentation*.

factor

pandas has a data type for categorical data.

```
cut(c(1,2,3,4,5,6), 3)
factor(c(1,2,3,2,2,3))
```

In pandas this is accomplished with `pd.cut` and `astype("category")`:

```
In [41]: pd.cut(pd.Series([1, 2, 3, 4, 5, 6]), 3)
Out[41]:
0    (0.995, 2.667]
1    (0.995, 2.667]
2    (2.667, 4.333]
3    (2.667, 4.333]
4      (4.333, 6.0]
5      (4.333, 6.0]
dtype: category
Categories (3, interval[float64]): [(0.995, 2.667] < (2.667, 4.333] < (4.333, 6.0]]
```

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```
In [42]: pd.Series([1, 2, 3, 2, 2, 3]).astype("category")
Out[42]:
0    1
1    2
2    3
3    2
4    2
5    3
dtype: category
Categories (3, int64): [1, 2, 3]
```

For more details and examples see *categorical introduction* and the *API documentation*. There is also a documentation regarding the *differences to R's factor*.

Comparison with SQL

Since many potential pandas users have some familiarity with SQL, this page is meant to provide some examples of how various SQL operations would be performed using pandas.

If you're new to pandas, you might want to first read through *10 Minutes to pandas* to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows:

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

Most of the examples will utilize the `tips` dataset found within pandas tests. We'll read the data into a DataFrame called `tips` and assume we have a database table of the same name and structure.

```
In [3]: url = (
   ...:     "https://raw.github.com/pandas-dev"
   ...:     "/pandas/master/pandas/tests/io/data/csv/tips.csv"
   ...: )
   ...:

In [4]: tips = pd.read_csv(url)

In [5]: tips.head()
Out[5]:
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
3       23.68  3.31    Male     No  Sun  Dinner     2
4       24.59  3.61  Female     No  Sun  Dinner     4
```

SELECT

In SQL, selection is done using a comma-separated list of columns you'd like to select (or a * to select all columns):

```
SELECT total_bill, tip, smoker, time
FROM tips
LIMIT 5;
```

With pandas, column selection is done by passing a list of column names to your DataFrame:

```
In [6]: tips[["total_bill", "tip", "smoker", "time"]].head(5)
Out[6]:
   total_bill   tip smoker    time
0       16.99  1.01     No  Dinner
1       10.34  1.66     No  Dinner
2       21.01  3.50     No  Dinner
3       23.68  3.31     No  Dinner
4       24.59  3.61     No  Dinner
```

Calling the DataFrame without the list of column names would display all columns (akin to SQL's *).

In SQL, you can add a calculated column:

```
SELECT *, tip/total_bill as tip_rate
FROM tips
LIMIT 5;
```

With pandas, you can use the *DataFrame.assign()* method of a DataFrame to append a new column:

```
In [7]: tips.assign(tip_rate=tips["tip"] / tips["total_bill"]).head(5)
Out[7]:
   total_bill   tip     sex smoker  day    time  size  tip_rate
0       16.99  1.01  Female     No  Sun  Dinner     2  0.059447
1       10.34  1.66    Male     No  Sun  Dinner     3  0.160542
2       21.01  3.50    Male     No  Sun  Dinner     3  0.166587
3       23.68  3.31    Male     No  Sun  Dinner     2  0.139780
4       24.59  3.61  Female     No  Sun  Dinner     4  0.146808
```

WHERE

Filtering in SQL is done via a WHERE clause.

```
SELECT *
FROM tips
WHERE time = 'Dinner'
LIMIT 5;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*

```
In [8]: tips[tips["time"] == "Dinner"].head(5)
Out[8]:
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
```

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```
3        23.68  3.31    Male     No   Sun  Dinner     2
4        24.59  3.61  Female     No   Sun  Dinner     4
```

The above statement is simply passing a `Series` of True/False objects to the DataFrame, returning all rows with True.

```
In [9]: is_dinner = tips["time"] == "Dinner"

In [10]: is_dinner.value_counts()
Out[10]:
True     176
False     68
Name: time, dtype: int64

In [11]: tips[is_dinner].head(5)
Out[11]:
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
3       23.68  3.31    Male     No  Sun  Dinner     2
4       24.59  3.61  Female     No  Sun  Dinner     4
```

Just like SQL's OR and AND, multiple conditions can be passed to a DataFrame using | (OR) and & (AND).

```
-- tips of more than $5.00 at Dinner meals
SELECT *
FROM tips
WHERE time = 'Dinner' AND tip > 5.00;
```

```
# tips of more than $5.00 at Dinner meals
In [12]: tips[(tips["time"] == "Dinner") & (tips["tip"] > 5.00)]
Out[12]:
     total_bill    tip     sex smoker  day    time  size
23         39.42   7.58    Male     No  Sat  Dinner     4
44         30.40   5.60    Male     No  Sun  Dinner     4
47         32.40   6.00    Male     No  Sun  Dinner     4
52         34.81   5.20  Female     No  Sun  Dinner     4
59         48.27   6.73    Male     No  Sat  Dinner     4
116        29.93   5.07    Male     No  Sun  Dinner     4
155        29.85   5.14  Female     No  Sun  Dinner     5
170        50.81  10.00    Male    Yes  Sat  Dinner     3
172         7.25   5.15    Male    Yes  Sun  Dinner     2
181        23.33   5.65    Male    Yes  Sun  Dinner     2
183        23.17   6.50    Male    Yes  Sun  Dinner     4
211        25.89   5.16    Male    Yes  Sat  Dinner     4
212        48.33   9.00    Male     No  Sat  Dinner     4
214        28.17   6.50  Female    Yes  Sat  Dinner     3
239        29.03   5.92    Male     No  Sat  Dinner     3
```

```
-- tips by parties of at least 5 diners OR bill total was more than $45
SELECT *
FROM tips
WHERE size >= 5 OR total_bill > 45;
```

```
# tips by parties of at least 5 diners OR bill total was more than $45
In [13]: tips[(tips["size"] >= 5) | (tips["total_bill"] > 45)]
Out[13]:
     total_bill    tip      sex smoker   day    time  size
59         48.27   6.73     Male     No   Sat  Dinner     4
125        29.80   4.20   Female     No  Thur   Lunch     6
141        34.30   6.70     Male     No  Thur   Lunch     6
142        41.19   5.00     Male     No  Thur   Lunch     5
143        27.05   5.00   Female     No  Thur   Lunch     6
155        29.85   5.14   Female     No   Sun  Dinner     5
156        48.17   5.00     Male     No   Sun  Dinner     6
170        50.81  10.00     Male    Yes   Sat  Dinner     3
182        45.35   3.50     Male    Yes   Sun  Dinner     3
185        20.69   5.00     Male     No   Sun  Dinner     5
187        30.46   2.00     Male    Yes   Sun  Dinner     5
212        48.33   9.00     Male     No   Sat  Dinner     4
216        28.15   3.00     Male    Yes   Sat  Dinner     5
```

NULL checking is done using the *notna()* and *isna()* methods.

```
In [14]: frame = pd.DataFrame(
   ....:     {"col1": ["A", "B", np.NaN, "C", "D"], "col2": ["F", np.NaN, "G", "H", "I
↪"]}
   ....: )
   ....:

In [15]: frame
Out[15]:
  col1 col2
0    A    F
1    B  NaN
2  NaN    G
3    C    H
4    D    I
```

Assume we have a table of the same structure as our DataFrame above. We can see only the records where `col2` IS NULL with the following query:

```
SELECT *
FROM frame
WHERE col2 IS NULL;
```

```
In [16]: frame[frame["col2"].isna()]
Out[16]:
  col1 col2
1    B  NaN
```

Getting items where `col1` IS NOT NULL can be done with *notna()*.

```
SELECT *
FROM frame
WHERE col1 IS NOT NULL;
```

```
In [17]: frame[frame["col1"].notna()]
Out[17]:
  col1 col2
```

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```
0    A    F
1    B  NaN
3    C    H
4    D    I
```

GROUP BY

In pandas, SQL's GROUP BY operations are performed using the similarly named *groupby()* method. *groupby()* typically refers to a process where we'd like to split a dataset into groups, apply some function (typically aggregation) , and then combine the groups together.

A common SQL operation would be getting the count of records in each group throughout a dataset. For instance, a query getting us the number of tips left by sex:

```
SELECT sex, count(*)
FROM tips
GROUP BY sex;
/*
Female     87
Male      157
*/
```

The pandas equivalent would be:

```
In [18]: tips.groupby("sex").size()
Out[18]:
sex
Female     87
Male      157
dtype: int64
```

Notice that in the pandas code we used *size()* and not *count()*. This is because *count()* applies the function to each column, returning the number of `not null` records within each.

```
In [19]: tips.groupby("sex").count()
Out[19]:
        total_bill  tip  smoker  day  time  size
sex
Female          87   87      87   87    87    87
Male           157  157     157  157   157   157
```

Alternatively, we could have applied the *count()* method to an individual column:

```
In [20]: tips.groupby("sex")["total_bill"].count()
Out[20]:
sex
Female     87
Male      157
Name: total_bill, dtype: int64
```

Multiple functions can also be applied at once. For instance, say we'd like to see how tip amount differs by day of the week - `agg()` allows you to pass a dictionary to your grouped DataFrame, indicating which functions to apply to specific columns.

```
SELECT day, AVG(tip), COUNT(*)
FROM tips
GROUP BY day;
/*
Fri   2.734737   19
Sat   2.993103   87
Sun   3.255132   76
Thur  2.771452   62
*/
```

```
In [21]: tips.groupby("day").agg({"tip": np.mean, "day": np.size})
Out[21]:
            tip  day
day
Fri    2.734737   19
Sat    2.993103   87
Sun    3.255132   76
Thur   2.771452   62
```

Grouping by more than one column is done by passing a list of columns to the `groupby()` method.

```
SELECT smoker, day, COUNT(*), AVG(tip)
FROM tips
GROUP BY smoker, day;
/*
smoker day
No     Fri      4  2.812500
       Sat     45  3.102889
       Sun     57  3.167895
       Thur    45  2.673778
Yes    Fri     15  2.714000
       Sat     42  2.875476
       Sun     19  3.516842
       Thur    17  3.030000
*/
```

```
In [22]: tips.groupby(["smoker", "day"]).agg({"tip": [np.size, np.mean]})
Out[22]:
               tip
              size      mean
smoker day
No     Fri     4.0  2.812500
       Sat    45.0  3.102889
       Sun    57.0  3.167895
       Thur   45.0  2.673778
Yes    Fri    15.0  2.714000
       Sat    42.0  2.875476
       Sun    19.0  3.516842
       Thur   17.0  3.030000
```

JOIN

JOINs can be performed with *join()* or *merge()*. By default, *join()* will join the DataFrames on their indices. Each method has parameters allowing you to specify the type of join to perform (LEFT, RIGHT, INNER, FULL) or the columns to join on (column names or indices).

```
In [23]: df1 = pd.DataFrame({"key": ["A", "B", "C", "D"], "value": np.random.randn(4)}
↪)

In [24]: df2 = pd.DataFrame({"key": ["B", "D", "D", "E"], "value": np.random.randn(4)}
↪)
```

Assume we have two database tables of the same name and structure as our DataFrames.

Now let's go over the various types of JOINs.

INNER JOIN

```
SELECT *
FROM df1
INNER JOIN df2
  ON df1.key = df2.key;
```

```
# merge performs an INNER JOIN by default
In [25]: pd.merge(df1, df2, on="key")
Out[25]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
```

merge() also offers parameters for cases when you'd like to join one DataFrame's column with another DataFrame's index.

```
In [26]: indexed_df2 = df2.set_index("key")

In [27]: pd.merge(df1, indexed_df2, left_on="key", right_index=True)
Out[27]:
  key   value_x   value_y
1   B -0.282863  1.212112
3   D -1.135632 -0.173215
3   D -1.135632  0.119209
```

LEFT OUTER JOIN

```
-- show all records from df1
SELECT *
FROM df1
LEFT OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from df1
In [28]: pd.merge(df1, df2, on="key", how="left")
Out[28]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
```

RIGHT JOIN

```
-- show all records from df2
SELECT *
FROM df1
RIGHT OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from df2
In [29]: pd.merge(df1, df2, on="key", how="right")
Out[29]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
3   E       NaN -1.044236
```

FULL JOIN

pandas also allows for FULL JOINs, which display both sides of the dataset, whether or not the joined columns find a match. As of writing, FULL JOINs are not supported in all RDBMS (MySQL).

```
-- show all records from both tables
SELECT *
FROM df1
FULL OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from both frames
In [30]: pd.merge(df1, df2, on="key", how="outer")
Out[30]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236
```

UNION

UNION ALL can be performed using *concat()*.

```
In [31]: df1 = pd.DataFrame(
   ....:     {"city": ["Chicago", "San Francisco", "New York City"], "rank": range(1,␣
↪4)}
   ....: )
   ....:

In [32]: df2 = pd.DataFrame(
   ....:     {"city": ["Chicago", "Boston", "Los Angeles"], "rank": [1, 4, 5]}
   ....: )
   ....:
```

```
SELECT city, rank
FROM df1
UNION ALL
SELECT city, rank
FROM df2;
/*
         city  rank
      Chicago     1
San Francisco     2
New York City     3
      Chicago     1
       Boston     4
  Los Angeles     5
*/
```

```
In [33]: pd.concat([df1, df2])
Out[33]:
             city  rank
0         Chicago     1
1   San Francisco     2
2   New York City     3
0         Chicago     1
1          Boston     4
2     Los Angeles     5
```

SQL's UNION is similar to UNION ALL, however UNION will remove duplicate rows.

```
SELECT city, rank
FROM df1
UNION
SELECT city, rank
FROM df2;
-- notice that there is only one Chicago record this time
/*
         city  rank
      Chicago     1
San Francisco     2
New York City     3
       Boston     4
  Los Angeles     5
*/
```

In pandas, you can use *concat()* in conjunction with *drop_duplicates()*.

```
In [34]: pd.concat([df1, df2]).drop_duplicates()
Out[34]:
            city  rank
0        Chicago     1
1  San Francisco     2
2  New York City     3
1         Boston     4
2    Los Angeles     5
```

pandas equivalents for some SQL analytic and aggregate functions

Top n rows with offset

```
-- MySQL
SELECT * FROM tips
ORDER BY tip DESC
LIMIT 10 OFFSET 5;
```

```
In [35]: tips.nlargest(10 + 5, columns="tip").tail(10)
Out[35]:
     total_bill   tip     sex smoker   day    time  size
183       23.17  6.50    Male    Yes   Sun  Dinner     4
214       28.17  6.50  Female    Yes   Sat  Dinner     3
47        32.40  6.00    Male     No   Sun  Dinner     4
239       29.03  5.92    Male     No   Sat  Dinner     3
88        24.71  5.85    Male     No  Thur   Lunch     2
181       23.33  5.65    Male    Yes   Sun  Dinner     2
44        30.40  5.60    Male     No   Sun  Dinner     4
52        34.81  5.20  Female     No   Sun  Dinner     4
85        34.83  5.17  Female     No  Thur   Lunch     4
211       25.89  5.16    Male    Yes   Sat  Dinner     4
```

Top n rows per group

```
-- Oracle's ROW_NUMBER() analytic function
SELECT * FROM (
  SELECT
    t.*,
    ROW_NUMBER() OVER(PARTITION BY day ORDER BY total_bill DESC) AS rn
  FROM tips t
)
WHERE rn < 3
ORDER BY day, rn;
```

```
In [36]: (
   ....:     tips.assign(
   ....:         rn=tips.sort_values(["total_bill"], ascending=False)
   ....:         .groupby(["day"])
   ....:         .cumcount()
   ....:         + 1
   ....:     )
   ....:     .query("rn < 3")
```

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```
   ....:     .sort_values(["day", "rn"])
   ....: )
   ....:
Out[36]:
     total_bill    tip     sex smoker   day    time  size  rn
95        40.17   4.73    Male    Yes   Fri  Dinner     4   1
90        28.97   3.00    Male    Yes   Fri  Dinner     2   2
170       50.81  10.00    Male    Yes   Sat  Dinner     3   1
212       48.33   9.00    Male     No   Sat  Dinner     4   2
156       48.17   5.00    Male     No   Sun  Dinner     6   1
182       45.35   3.50    Male    Yes   Sun  Dinner     3   2
197       43.11   5.00  Female    Yes  Thur   Lunch     4   1
142       41.19   5.00    Male     No  Thur   Lunch     5   2
```

the same using `rank(method='first')` function

```
In [37]: (
   ....:     tips.assign(
   ....:         rnk=tips.groupby(["day"])["total_bill"].rank(
   ....:             method="first", ascending=False
   ....:         )
   ....:     )
   ....:     .query("rnk < 3")
   ....:     .sort_values(["day", "rnk"])
   ....: )
   ....:
Out[37]:
     total_bill    tip     sex smoker   day    time  size  rnk
95        40.17   4.73    Male    Yes   Fri  Dinner     4  1.0
90        28.97   3.00    Male    Yes   Fri  Dinner     2  2.0
170       50.81  10.00    Male    Yes   Sat  Dinner     3  1.0
212       48.33   9.00    Male     No   Sat  Dinner     4  2.0
156       48.17   5.00    Male     No   Sun  Dinner     6  1.0
182       45.35   3.50    Male    Yes   Sun  Dinner     3  2.0
197       43.11   5.00  Female    Yes  Thur   Lunch     4  1.0
142       41.19   5.00    Male     No  Thur   Lunch     5  2.0
```

```
-- Oracle's RANK() analytic function
SELECT * FROM (
  SELECT
    t.*,
    RANK() OVER(PARTITION BY sex ORDER BY tip) AS rnk
  FROM tips t
  WHERE tip < 2
)
WHERE rnk < 3
ORDER BY sex, rnk;
```

Let's find tips with (rank < 3) per gender group for (tips < 2). Notice that when using `rank(method='min')` function `rnk_min` remains the same for the same `tip` (as Oracle's RANK() function)

```
In [38]: (
   ....:     tips[tips["tip"] < 2]
   ....:     .assign(rnk_min=tips.groupby(["sex"])["tip"].rank(method="min"))
   ....:     .query("rnk_min < 3")
   ....:     .sort_values(["sex", "rnk_min"])
```

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```
   ....: )
   ....:
Out[38]:
     total_bill   tip     sex smoker  day    time  size  rnk_min
67         3.07  1.00  Female    Yes  Sat  Dinner     1      1.0
92         5.75  1.00  Female    Yes  Fri  Dinner     2      1.0
111        7.25  1.00  Female     No  Sat  Dinner     1      1.0
236       12.60  1.00    Male    Yes  Sat  Dinner     2      1.0
237       32.83  1.17    Male    Yes  Sat  Dinner     2      2.0
```

UPDATE

```
UPDATE tips
SET tip = tip*2
WHERE tip < 2;
```

```
In [39]: tips.loc[tips["tip"] < 2, "tip"] *= 2
```

DELETE

```
DELETE FROM tips
WHERE tip > 9;
```

In pandas we select the rows that should remain, instead of deleting them

```
In [40]: tips = tips.loc[tips["tip"] <= 9]
```

Comparison with SAS

For potential users coming from SAS this page is meant to demonstrate how different SAS operations would be performed in pandas.

If you're new to pandas, you might want to first read through *10 Minutes to pandas* to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows:

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

Note: Throughout this tutorial, the pandas `DataFrame` will be displayed by calling `df.head()`, which displays the first N (default 5) rows of the `DataFrame`. This is often used in interactive work (e.g. Jupyter notebook or terminal) - the equivalent in SAS would be:

```
proc print data=df(obs=5);
run;
```

Data structures

General terminology translation

pandas	SAS
`DataFrame`	data set
column	variable
row	observation
groupby	BY-group
`NaN`	.

`DataFrame` / `Series`

A `DataFrame` in pandas is analogous to a SAS data set - a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set using SAS's `DATA` step, can also be accomplished in pandas.

A `Series` is the data structure that represents one column of a `DataFrame`. SAS doesn't have a separate data structure for a single column, but in general, working with a `Series` is analogous to referencing a column in the `DATA` step.

`Index`

Every `DataFrame` and `Series` has an `Index` - which are labels on the *rows* of the data. SAS does not have an exactly analogous concept. A data set's rows are essentially unlabeled, other than an implicit integer index that can be accessed during the `DATA` step (`_N_`).

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled `Index` or `MultiIndex` can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the `Index` and just treat the `DataFrame` as a collection of columns. Please see the *indexing documentation* for much more on how to use an `Index` effectively.

Data input / output

Constructing a DataFrame from values

A SAS data set can be built from specified values by placing the data after a `datalines` statement and specifying the column names.

```
data df;
    input x y;
    datalines;
    1 2
    3 4
    5 6
    ;
run;
```

A pandas `DataFrame` can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```
In [3]: df = pd.DataFrame({"x": [1, 3, 5], "y": [2, 4, 6]})

In [4]: df
Out[4]:
   x  y
0  1  2
1  3  4
2  5  6
```

Reading external data

Like SAS, pandas provides utilities for reading in data from many formats. The `tips` dataset, found within the pandas tests (csv) will be used in many of the following examples.

SAS provides `PROC IMPORT` to read csv data into a data set.

```
proc import datafile='tips.csv' dbms=csv out=tips replace;
    getnames=yes;
run;
```

The pandas method is *`read_csv()`*, which works similarly.

```
In [5]: url = (
   ...:     "https://raw.github.com/pandas-dev/"
   ...:     "pandas/master/pandas/tests/io/data/csv/tips.csv"
   ...: )
   ...:

In [6]: tips = pd.read_csv(url)

In [7]: tips.head()
Out[7]:
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
3       23.68  3.31    Male     No  Sun  Dinner     2
4       24.59  3.61  Female     No  Sun  Dinner     4
```

Like `PROC IMPORT`, `read_csv` can take a number of parameters to specify how the data should be parsed. For example, if the data was instead tab delimited, and did not have column names, the pandas command would be:

```
tips = pd.read_csv("tips.csv", sep="\t", header=None)

# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table("tips.csv", header=None)
```

In addition to text/csv, pandas supports a variety of other data formats such as Excel, HDF5, and SQL databases. These are all read via a `pd.read_*` function. See the *IO documentation* for more details.

Exporting data

The inverse of `PROC IMPORT` in SAS is `PROC EXPORT`

```
proc export data=tips outfile='tips2.csv' dbms=csv;
run;
```

Similarly in pandas, the opposite of `read_csv` is *`to_csv()`*, and other data formats follow a similar api.

```
tips.to_csv("tips2.csv")
```

Data operations

Operations on columns

In the `DATA` step, arbitrary math expressions can be used on new or existing columns.

```
data tips;
    set tips;
    total_bill = total_bill - 2;
    new_bill = total_bill / 2;
run;
```

pandas provides similar vectorized operations by specifying the individual `Series` in the `DataFrame`. New columns can be assigned in the same way.

```
In [8]: tips["total_bill"] = tips["total_bill"] - 2

In [9]: tips["new_bill"] = tips["total_bill"] / 2.0

In [10]: tips.head()
Out[10]:
   total_bill   tip     sex smoker  day    time  size  new_bill
0       14.99  1.01  Female     No  Sun  Dinner     2     7.495
1        8.34  1.66    Male     No  Sun  Dinner     3     4.170
2       19.01  3.50    Male     No  Sun  Dinner     3     9.505
3       21.68  3.31    Male     No  Sun  Dinner     2    10.840
4       22.59  3.61  Female     No  Sun  Dinner     4    11.295
```

Filtering

Filtering in SAS is done with an `if` or `where` statement, on one or more columns.

```
data tips;
    set tips;
    if total_bill > 10;
run;

data tips;
    set tips;
    where total_bill > 10;
    /* equivalent in this case - where happens before the
       DATA step begins and can also be used in PROC statements */
run;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*

```
In [11]: tips[tips["total_bill"] > 10].head()
Out[11]:
   total_bill   tip     sex smoker  day    time  size
0       14.99  1.01  Female     No  Sun  Dinner     2
2       19.01  3.50    Male     No  Sun  Dinner     3
3       21.68  3.31    Male     No  Sun  Dinner     2
4       22.59  3.61  Female     No  Sun  Dinner     4
5       23.29  4.71    Male     No  Sun  Dinner     4
```

If/then logic

In SAS, if/then logic can be used to create new columns.

```
data tips;
    set tips;
    format bucket $4.;

    if total_bill < 10 then bucket = 'low';
    else bucket = 'high';
run;
```

The same operation in pandas can be accomplished using the `where` method from `numpy`.

```
In [12]: tips["bucket"] = np.where(tips["total_bill"] < 10, "low", "high")

In [13]: tips.head()
Out[13]:
   total_bill   tip     sex smoker  day    time  size bucket
0       14.99  1.01  Female     No  Sun  Dinner     2   high
1        8.34  1.66    Male     No  Sun  Dinner     3    low
2       19.01  3.50    Male     No  Sun  Dinner     3   high
3       21.68  3.31    Male     No  Sun  Dinner     2   high
4       22.59  3.61  Female     No  Sun  Dinner     4   high
```

Date functionality

SAS provides a variety of functions to do operations on date/datetime columns.

```
data tips;
    set tips;
    format date1 date2 date1_plusmonth mmddyy10.;
    date1 = mdy(1, 15, 2013);
    date2 = mdy(2, 15, 2015);
    date1_year = year(date1);
    date2_month = month(date2);
    * shift date to beginning of next interval;
    date1_next = intnx('MONTH', date1, 1);
    * count intervals between dates;
    months_between = intck('MONTH', date1, date2);
run;
```

The equivalent pandas operations are shown below. In addition to these functions pandas supports other Time Series features not available in Base SAS (such as resampling and custom offsets) - see the *timeseries documentation* for

more details.

```
In [14]: tips["date1"] = pd.Timestamp("2013-01-15")

In [15]: tips["date2"] = pd.Timestamp("2015-02-15")

In [16]: tips["date1_year"] = tips["date1"].dt.year

In [17]: tips["date2_month"] = tips["date2"].dt.month

In [18]: tips["date1_next"] = tips["date1"] + pd.offsets.MonthBegin()

In [19]: tips["months_between"] = tips["date2"].dt.to_period("M") - tips[
   ....:     "date1"
   ....: ].dt.to_period("M")
   ....:

In [20]: tips[
   ....:     ["date1", "date2", "date1_year", "date2_month", "date1_next", "months_
↪between"]
   ....: ].head()
   ....:
Out[20]:
       date1      date2  date1_year  date2_month date1_next    months_between
0 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
1 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
2 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
3 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
4 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
```

Selection of columns

SAS provides keywords in the `DATA` step to select, drop, and rename columns.

```
data tips;
    set tips;
    keep sex total_bill tip;
run;

data tips;
    set tips;
    drop sex;
run;

data tips;
    set tips;
    rename total_bill=total_bill_2;
run;
```

The same operations are expressed in pandas below.

```
# keep
In [21]: tips[["sex", "total_bill", "tip"]].head()
Out[21]:
      sex  total_bill   tip
0  Female       14.99  1.01
```

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```
1    Male        8.34  1.66
2    Male       19.01  3.50
3    Male       21.68  3.31
4  Female       22.59  3.61

# drop
In [22]: tips.drop("sex", axis=1).head()
Out[22]:
   total_bill   tip smoker  day    time  size
0       14.99  1.01     No  Sun  Dinner     2
1        8.34  1.66     No  Sun  Dinner     3
2       19.01  3.50     No  Sun  Dinner     3
3       21.68  3.31     No  Sun  Dinner     2
4       22.59  3.61     No  Sun  Dinner     4

# rename
In [23]: tips.rename(columns={"total_bill": "total_bill_2"}).head()
Out[23]:
   total_bill_2   tip     sex smoker  day    time  size
0         14.99  1.01  Female     No  Sun  Dinner     2
1          8.34  1.66    Male     No  Sun  Dinner     3
2         19.01  3.50    Male     No  Sun  Dinner     3
3         21.68  3.31    Male     No  Sun  Dinner     2
4         22.59  3.61  Female     No  Sun  Dinner     4
```

Sorting by values

Sorting in SAS is accomplished via `PROC SORT`

```
proc sort data=tips;
    by sex total_bill;
run;
```

pandas objects have a *`sort_values()`* method, which takes a list of columns to sort by.

```
In [24]: tips = tips.sort_values(["sex", "total_bill"])

In [25]: tips.head()
Out[25]:
     total_bill   tip     sex smoker   day    time  size
67         1.07  1.00  Female    Yes   Sat  Dinner     1
92         3.75  1.00  Female    Yes   Fri  Dinner     2
111        5.25  1.00  Female     No   Sat  Dinner     1
145        6.35  1.50  Female     No  Thur   Lunch     2
135        6.51  1.25  Female     No  Thur   Lunch     2
```

String processing

Length

SAS determines the length of a character string with the LENGTHN and LENGTHC functions. `LENGTHN` excludes trailing blanks and `LENGTHC` includes trailing blanks.

```
data _null_;
set tips;
put(LENGTHN(time));
put(LENGTHC(time));
run;
```

Python determines the length of a character string with the `len` function. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

```
In [26]: tips["time"].str.len().head()
Out[26]:
67     6
92     6
111    6
145    5
135    5
Name: time, dtype: int64

In [27]: tips["time"].str.rstrip().str.len().head()
Out[27]:
67     6
92     6
111    6
145    5
135    5
Name: time, dtype: int64
```

Find

SAS determines the position of a character in a string with the FINDW function. `FINDW` takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```
data _null_;
set tips;
put(FINDW(sex,'ale'));
run;
```

Python determines the position of a character in a string with the `find` function. `find` searches for the first position of the substring. If the substring is found, the function returns its position. Keep in mind that Python indexes are zero-based and the function will return -1 if it fails to find the substring.

```
In [28]: tips["sex"].str.find("ale").head()
Out[28]:
67     3
92     3
111    3
145    3
```

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```
135    3
Name: sex, dtype: int64
```

Substring

SAS extracts a substring from a string based on its position with the SUBSTR function.

```
data _null_;
set tips;
put(substr(sex,1,1));
run;
```

With pandas you can use `[]` notation to extract a substring from a string by position locations. Keep in mind that Python indexes are zero-based.

```
In [29]: tips["sex"].str[0:1].head()
Out[29]:
67     F
92     F
111    F
145    F
135    F
Name: sex, dtype: object
```

Scan

The SAS SCAN function returns the nth word from a string. The first argument is the string you want to parse and the second argument specifies which word you want to extract.

```
data firstlast;
input String $60.;
First_Name = scan(string, 1);
Last_Name = scan(string, -1);
datalines2;
John Smith;
Jane Cook;
;;;
run;
```

Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.

```
In [30]: firstlast = pd.DataFrame({"String": ["John Smith", "Jane Cook"]})

In [31]: firstlast["First_Name"] = firstlast["String"].str.split(" ", expand=True)[0]

In [32]: firstlast["Last_Name"] = firstlast["String"].str.rsplit(" ", expand=True)[0]

In [33]: firstlast
Out[33]:
       String First_Name Last_Name
0  John Smith       John      John
1   Jane Cook       Jane      Jane
```

Upcase, lowcase, and propcase

The SAS UPCASE LOWCASE and PROPCASE functions change the case of the argument.

```
data firstlast;
input String $60.;
string_up = UPCASE(string);
string_low = LOWCASE(string);
string_prop = PROPCASE(string);
datalines2;
John Smith;
Jane Cook;
;;;
run;
```

The equivalent Python functions are `upper`, `lower`, and `title`.

```
In [34]: firstlast = pd.DataFrame({"String": ["John Smith", "Jane Cook"]})

In [35]: firstlast["string_up"] = firstlast["String"].str.upper()

In [36]: firstlast["string_low"] = firstlast["String"].str.lower()

In [37]: firstlast["string_prop"] = firstlast["String"].str.title()

In [38]: firstlast
Out[38]:
       String   string_up  string_low string_prop
0  John Smith  JOHN SMITH  john smith  John Smith
1   Jane Cook   JANE COOK   jane cook   Jane Cook
```

Merging

The following tables will be used in the merge examples

```
In [39]: df1 = pd.DataFrame({"key": ["A", "B", "C", "D"], "value": np.random.randn(4)}
↪)

In [40]: df1
Out[40]:
  key     value
0   A  0.469112
1   B -0.282863
2   C -1.509059
3   D -1.135632

In [41]: df2 = pd.DataFrame({"key": ["B", "D", "D", "E"], "value": np.random.randn(4)}
↪)

In [42]: df2
Out[42]:
  key     value
0   B  1.212112
1   D -0.173215
2   D  0.119209
3   E -1.044236
```

In SAS, data must be explicitly sorted before merging. Different types of joins are accomplished using the `in=` dummy variables to track whether a match was found in one or both input frames.

```
proc sort data=df1;
    by key;
run;

proc sort data=df2;
    by key;
run;

data left_join inner_join right_join outer_join;
    merge df1(in=a) df2(in=b);

    if a and b then output inner_join;
    if a then output left_join;
    if b then output right_join;
    if a or b then output outer_join;
run;
```

pandas DataFrames have a *`merge()`* method, which provides similar functionality. Note that the data does not have to be sorted ahead of time, and different join types are accomplished via the `how` keyword.

```
In [43]: inner_join = df1.merge(df2, on=["key"], how="inner")

In [44]: inner_join
Out[44]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209

In [45]: left_join = df1.merge(df2, on=["key"], how="left")

In [46]: left_join
Out[46]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209

In [47]: right_join = df1.merge(df2, on=["key"], how="right")

In [48]: right_join
Out[48]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
3   E       NaN -1.044236

In [49]: outer_join = df1.merge(df2, on=["key"], how="outer")

In [50]: outer_join
Out[50]:
  key   value_x   value_y
```

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```
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236
```

Missing data

Like SAS, pandas has a representation for missing data - which is the special float value `NaN` (not a number). Many of the semantics are the same, for example missing data propagates through numeric operations, and is ignored by default for aggregations.

```
In [51]: outer_join
Out[51]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236

In [52]: outer_join["value_x"] + outer_join["value_y"]
Out[52]:
0         NaN
1    0.929249
2         NaN
3   -1.308847
4   -1.016424
5         NaN
dtype: float64

In [53]: outer_join["value_x"].sum()
Out[53]: -3.5940742896293765
```

One difference is that missing data cannot be compared to its sentinel value. For example, in SAS you could do this to filter missing values.

```
data outer_join_nulls;
    set outer_join;
    if value_x = .;
run;

data outer_join_no_nulls;
    set outer_join;
    if value_x ^= .;
run;
```

Which doesn't work in pandas. Instead, the `pd.isna` or `pd.notna` functions should be used for comparisons.

```
In [54]: outer_join[pd.isna(outer_join["value_x"])]
Out[54]:
  key  value_x   value_y
```

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```
5   E      NaN -1.044236
```

```
In [55]: outer_join[pd.notna(outer_join["value_x"])]
Out[55]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
```

pandas also provides a variety of methods to work with missing data - some of which would be challenging to express in SAS. For example, there are methods to drop all rows with any missing values, replacing missing values with a specified value, like the mean, or forward filling from previous rows. See the *missing data documentation* for more.

```
In [56]: outer_join.dropna()
Out[56]:
  key   value_x   value_y
1   B -0.282863  1.212112
3   D -1.135632 -0.173215
4   D -1.135632  0.119209

In [57]: outer_join.fillna(method="ffill")
Out[57]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059  1.212112
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E -1.135632 -1.044236

In [58]: outer_join["value_x"].fillna(outer_join["value_x"].mean())
Out[58]:
0    0.469112
1   -0.282863
2   -1.509059
3   -1.135632
4   -1.135632
5   -0.718815
Name: value_x, dtype: float64
```

GroupBy

Aggregation

SAS's PROC SUMMARY can be used to group by one or more key variables and compute aggregations on numeric columns.

```
proc summary data=tips nway;
    class sex smoker;
    var total_bill tip;
    output out=tips_summed sum=;
run;
```

pandas provides a flexible `groupby` mechanism that allows similar aggregations. See the *groupby documentation* for more details and examples.

```
In [59]: tips_summed = tips.groupby(["sex", "smoker"])[["total_bill", "tip"]].sum()

In [60]: tips_summed.head()
Out[60]:
               total_bill     tip
sex    smoker
Female No          869.68  149.77
       Yes         527.27   96.74
Male   No         1725.75  302.00
       Yes        1217.07  183.07
```

Transformation

In SAS, if the group aggregations need to be used with the original frame, it must be merged back together. For example, to subtract the mean for each observation by smoker group.

```
proc summary data=tips missing nway;
    class smoker;
    var total_bill;
    output out=smoker_means mean(total_bill)=group_bill;
run;

proc sort data=tips;
    by smoker;
run;

data tips;
    merge tips(in=a) smoker_means(in=b);
    by smoker;
    adj_total_bill = total_bill - group_bill;
    if a and b;
run;
```

pandas `groupby` provides a `transform` mechanism that allows these type of operations to be succinctly expressed in one operation.

```
In [61]: gb = tips.groupby("smoker")["total_bill"]

In [62]: tips["adj_total_bill"] = tips["total_bill"] - gb.transform("mean")

In [63]: tips.head()
Out[63]:
     total_bill   tip     sex smoker   day    time  size  adj_total_bill
67         1.07  1.00  Female    Yes   Sat  Dinner     1      -17.686344
92         3.75  1.00  Female    Yes   Fri  Dinner     2      -15.006344
111        5.25  1.00  Female     No   Sat  Dinner     1      -11.938278
145        6.35  1.50  Female     No  Thur   Lunch     2      -10.838278
135        6.51  1.25  Female     No  Thur   Lunch     2      -10.678278
```

By group processing

In addition to aggregation, pandas `groupby` can be used to replicate most other by group processing from SAS. For example, this `DATA` step reads the data by sex/smoker group and filters to the first entry for each.

```
proc sort data=tips;
   by sex smoker;
run;

data tips_first;
    set tips;
    by sex smoker;
    if FIRST.sex or FIRST.smoker then output;
run;
```

In pandas this would be written as:

```
In [64]: tips.groupby(["sex", "smoker"]).first()
Out[64]:
               total_bill   tip   day    time  size  adj_total_bill
sex    smoker
Female No            5.25  1.00   Sat  Dinner     1      -11.938278
       Yes           1.07  1.00   Sat  Dinner     1      -17.686344
Male   No            5.51  2.00  Thur   Lunch     2      -11.678278
       Yes           5.25  5.15   Sun  Dinner     2      -13.506344
```

Other considerations

Disk vs memory

pandas operates exclusively in memory, where a SAS data set exists on disk. This means that the size of data able to be loaded in pandas is limited by your machine's memory, but also that the operations on that data may be faster.

If out of core processing is needed, one possibility is the dask.dataframe library (currently in development) which provides a subset of pandas functionality for an on-disk `DataFrame`

Data interop

pandas provides a *`read_sas()`* method that can read SAS data saved in the XPORT or SAS7BDAT binary format.

```
libname xportout xport 'transport-file.xpt';
data xportout.tips;
    set tips(rename=(total_bill=tbill));
    * xport variable names limited to 6 characters;
run;
```

```
df = pd.read_sas("transport-file.xpt")
df = pd.read_sas("binary-file.sas7bdat")
```

You can also specify the file format directly. By default, pandas will try to infer the file format based on its extension.

```
df = pd.read_sas("transport-file.xpt", format="xport")
df = pd.read_sas("binary-file.sas7bdat", format="sas7bdat")
```

XPORT is a relatively limited format and the parsing of it is not as optimized as some of the other pandas readers. An alternative way to interop data between SAS and pandas is to serialize to csv.

```
# version 0.17, 10M rows

In [8]: %time df = pd.read_sas('big.xpt')
Wall time: 14.6 s

In [9]: %time df = pd.read_csv('big.csv')
Wall time: 4.86 s
```

Comparison with Stata

For potential users coming from Stata this page is meant to demonstrate how different Stata operations would be performed in pandas.

If you're new to pandas, you might want to first read through *10 Minutes to pandas* to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows. This means that we can refer to the libraries as `pd` and `np`, respectively, for the rest of the document.

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

Note: Throughout this tutorial, the pandas `DataFrame` will be displayed by calling `df.head()`, which displays the first N (default 5) rows of the `DataFrame`. This is often used in interactive work (e.g. Jupyter notebook or terminal) – the equivalent in Stata would be:

```
list in 1/5
```

Data structures

General terminology translation

pandas	Stata
`DataFrame`	data set
column	variable
row	observation
groupby	bysort
`NaN`	.

DataFrame / Series

A DataFrame in pandas is analogous to a Stata data set – a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set in Stata can also be accomplished in pandas.

A Series is the data structure that represents one column of a DataFrame. Stata doesn't have a separate data structure for a single column, but in general, working with a Series is analogous to referencing a column of a data set in Stata.

Index

Every DataFrame and Series has an Index – labels on the *rows* of the data. Stata does not have an exactly analogous concept. In Stata, a data set's rows are essentially unlabeled, other than an implicit integer index that can be accessed with _n.

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled Index or MultiIndex can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the Index and just treat the DataFrame as a collection of columns. Please see the *indexing documentation* for much more on how to use an Index effectively.

Data input / output

Constructing a DataFrame from values

A Stata data set can be built from specified values by placing the data after an input statement and specifying the column names.

```
input x y
1 2
3 4
5 6
end
```

A pandas DataFrame can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```
In [3]: df = pd.DataFrame({"x": [1, 3, 5], "y": [2, 4, 6]})

In [4]: df
Out[4]:
   x  y
0  1  2
1  3  4
2  5  6
```

Reading external data

Like Stata, pandas provides utilities for reading in data from many formats. The `tips` data set, found within the pandas tests (csv) will be used in many of the following examples.

Stata provides `import delimited` to read csv data into a data set in memory. If the `tips.csv` file is in the current working directory, we can import it as follows.

```
import delimited tips.csv
```

The pandas method is *`read_csv()`*, which works similarly. Additionally, it will automatically download the data set if presented with a url.

```
In [5]: url = (
   ...:     "https://raw.github.com/pandas-dev"
   ...:     "/pandas/master/pandas/tests/io/data/csv/tips.csv"
   ...: )
   ...:

In [6]: tips = pd.read_csv(url)

In [7]: tips.head()
Out[7]:
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
3       23.68  3.31    Male     No  Sun  Dinner     2
4       24.59  3.61  Female     No  Sun  Dinner     4
```

Like `import delimited`, *`read_csv()`* can take a number of parameters to specify how the data should be parsed. For example, if the data were instead tab delimited, did not have column names, and existed in the current working directory, the pandas command would be:

```
tips = pd.read_csv("tips.csv", sep="\t", header=None)

# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table("tips.csv", header=None)
```

pandas can also read Stata data sets in `.dta` format with the *`read_stata()`* function.

```
df = pd.read_stata("data.dta")
```

In addition to text/csv and Stata files, pandas supports a variety of other data formats such as Excel, SAS, HDF5, Parquet, and SQL databases. These are all read via a `pd.read_*` function. See the *IO documentation* for more details.

Exporting data

The inverse of `import delimited` in Stata is `export delimited`

```
export delimited tips2.csv
```

Similarly in pandas, the opposite of `read_csv` is *DataFrame.to_csv()*.

```
tips.to_csv("tips2.csv")
```

pandas can also export to Stata file format with the *DataFrame.to_stata()* method.

```
tips.to_stata("tips2.dta")
```

Data operations

Operations on columns

In Stata, arbitrary math expressions can be used with the `generate` and `replace` commands on new or existing columns. The `drop` command drops the column from the data set.

```
replace total_bill = total_bill - 2
generate new_bill = total_bill / 2
drop new_bill
```

pandas provides similar vectorized operations by specifying the individual `Series` in the `DataFrame`. New columns can be assigned in the same way. The *DataFrame.drop()* method drops a column from the `DataFrame`.

```
In [8]: tips["total_bill"] = tips["total_bill"] - 2

In [9]: tips["new_bill"] = tips["total_bill"] / 2

In [10]: tips.head()
Out[10]:
   total_bill   tip     sex smoker  day    time  size  new_bill
0       14.99  1.01  Female     No  Sun  Dinner     2     7.495
1        8.34  1.66    Male     No  Sun  Dinner     3     4.170
2       19.01  3.50    Male     No  Sun  Dinner     3     9.505
3       21.68  3.31    Male     No  Sun  Dinner     2    10.840
4       22.59  3.61  Female     No  Sun  Dinner     4    11.295

In [11]: tips = tips.drop("new_bill", axis=1)
```

Filtering

Filtering in Stata is done with an `if` clause on one or more columns.

```
list if total_bill > 10
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*.

```
In [12]: tips[tips["total_bill"] > 10].head()
Out[12]:
   total_bill   tip     sex smoker  day    time  size
0       14.99  1.01  Female     No  Sun  Dinner     2
2       19.01  3.50    Male     No  Sun  Dinner     3
3       21.68  3.31    Male     No  Sun  Dinner     2
4       22.59  3.61  Female     No  Sun  Dinner     4
5       23.29  4.71    Male     No  Sun  Dinner     4
```

If/then logic

In Stata, an `if` clause can also be used to create new columns.

```
generate bucket = "low" if total_bill < 10
replace bucket = "high" if total_bill >= 10
```

The same operation in pandas can be accomplished using the `where` method from `numpy`.

```
In [13]: tips["bucket"] = np.where(tips["total_bill"] < 10, "low", "high")

In [14]: tips.head()
Out[14]:
   total_bill   tip     sex smoker  day    time  size bucket
0       14.99  1.01  Female     No  Sun  Dinner     2   high
1        8.34  1.66    Male     No  Sun  Dinner     3    low
2       19.01  3.50    Male     No  Sun  Dinner     3   high
3       21.68  3.31    Male     No  Sun  Dinner     2   high
4       22.59  3.61  Female     No  Sun  Dinner     4   high
```

Date functionality

Stata provides a variety of functions to do operations on date/datetime columns.

```
generate date1 = mdy(1, 15, 2013)
generate date2 = date("Feb152015", "MDY")

generate date1_year = year(date1)
generate date2_month = month(date2)

* shift date to beginning of next month
generate date1_next = mdy(month(date1) + 1, 1, year(date1)) if month(date1) != 12
replace date1_next = mdy(1, 1, year(date1) + 1) if month(date1) == 12
generate months_between = mofd(date2) - mofd(date1)

list date1 date2 date1_year date2_month date1_next months_between
```

The equivalent pandas operations are shown below. In addition to these functions, pandas supports other Time Series features not available in Stata (such as time zone handling and custom offsets) – see the *timeseries documentation* for more details.

```
In [15]: tips["date1"] = pd.Timestamp("2013-01-15")

In [16]: tips["date2"] = pd.Timestamp("2015-02-15")
```

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```
In [17]: tips["date1_year"] = tips["date1"].dt.year

In [18]: tips["date2_month"] = tips["date2"].dt.month

In [19]: tips["date1_next"] = tips["date1"] + pd.offsets.MonthBegin()

In [20]: tips["months_between"] = tips["date2"].dt.to_period("M") - tips[
   ....:     "date1"
   ....: ].dt.to_period("M")
   ....:

In [21]: tips[
   ....:     ["date1", "date2", "date1_year", "date2_month", "date1_next", "months_
↪between"]
   ....: ].head()
   ....:
Out[21]:
       date1      date2  date1_year  date2_month date1_next    months_between
0 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
1 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
2 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
3 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
4 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
```

Selection of columns

Stata provides keywords to select, drop, and rename columns.

```
keep sex total_bill tip

drop sex

rename total_bill total_bill_2
```

The same operations are expressed in pandas below. Note that in contrast to Stata, these operations do not happen in place. To make these changes persist, assign the operation back to a variable.

```
# keep
In [22]: tips[["sex", "total_bill", "tip"]].head()
Out[22]:
      sex  total_bill   tip
0  Female       14.99  1.01
1    Male        8.34  1.66
2    Male       19.01  3.50
3    Male       21.68  3.31
4  Female       22.59  3.61

# drop
In [23]: tips.drop("sex", axis=1).head()
Out[23]:
   total_bill   tip smoker  day    time  size
0       14.99  1.01     No  Sun  Dinner     2
1        8.34  1.66     No  Sun  Dinner     3
2       19.01  3.50     No  Sun  Dinner     3
```

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```
3       21.68  3.31     No  Sun  Dinner     2
4       22.59  3.61     No  Sun  Dinner     4

# rename
In [24]: tips.rename(columns={"total_bill": "total_bill_2"}).head()
Out[24]:
   total_bill_2   tip     sex smoker  day    time  size
0         14.99  1.01  Female     No  Sun  Dinner     2
1          8.34  1.66    Male     No  Sun  Dinner     3
2         19.01  3.50    Male     No  Sun  Dinner     3
3         21.68  3.31    Male     No  Sun  Dinner     2
4         22.59  3.61  Female     No  Sun  Dinner     4
```

Sorting by values

Sorting in Stata is accomplished via `sort`

```
sort sex total_bill
```

pandas objects have a *`DataFrame.sort_values()`* method, which takes a list of columns to sort by.

```
In [25]: tips = tips.sort_values(["sex", "total_bill"])

In [26]: tips.head()
Out[26]:
     total_bill   tip     sex smoker   day    time  size
67         1.07  1.00  Female    Yes   Sat  Dinner     1
92         3.75  1.00  Female    Yes   Fri  Dinner     2
111        5.25  1.00  Female     No   Sat  Dinner     1
145        6.35  1.50  Female     No  Thur   Lunch     2
135        6.51  1.25  Female     No  Thur   Lunch     2
```

String processing

Finding length of string

Stata determines the length of a character string with the `strlen()` and `ustrlen()` functions for ASCII and Unicode strings, respectively.

```
generate strlen_time = strlen(time)
generate ustrlen_time = ustrlen(time)
```

Python determines the length of a character string with the `len` function. In Python 3, all strings are Unicode strings. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

```
In [27]: tips["time"].str.len().head()
Out[27]:
67     6
92     6
111    6
145    5
135    5
```

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```
Name: time, dtype: int64

In [28]: tips["time"].str.rstrip().str.len().head()
Out[28]:
67     6
92     6
111    6
145    5
135    5
Name: time, dtype: int64
```

Finding position of substring

Stata determines the position of a character in a string with the `strpos()` function. This takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```
generate str_position = strpos(sex, "ale")
```

Python determines the position of a character in a string with the `find()` function. `find` searches for the first position of the substring. If the substring is found, the function returns its position. Keep in mind that Python indexes are zero-based and the function will return -1 if it fails to find the substring.

```
In [29]: tips["sex"].str.find("ale").head()
Out[29]:
67     3
92     3
111    3
145    3
135    3
Name: sex, dtype: int64
```

Extracting substring by position

Stata extracts a substring from a string based on its position with the `substr()` function.

```
generate short_sex = substr(sex, 1, 1)
```

With pandas you can use `[]` notation to extract a substring from a string by position locations. Keep in mind that Python indexes are zero-based.

```
In [30]: tips["sex"].str[0:1].head()
Out[30]:
67     F
92     F
111    F
145    F
135    F
Name: sex, dtype: object
```

Extracting nth word

The Stata `word()` function returns the nth word from a string. The first argument is the string you want to parse and the second argument specifies which word you want to extract.

```
clear
input str20 string
"John Smith"
"Jane Cook"
end

generate first_name = word(name, 1)
generate last_name = word(name, -1)
```

Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.

```
In [31]: firstlast = pd.DataFrame({"string": ["John Smith", "Jane Cook"]})

In [32]: firstlast["First_Name"] = firstlast["string"].str.split(" ", expand=True)[0]

In [33]: firstlast["Last_Name"] = firstlast["string"].str.rsplit(" ", expand=True)[0]

In [34]: firstlast
Out[34]:
       string First_Name Last_Name
0  John Smith       John      John
1   Jane Cook       Jane      Jane
```

Changing case

The Stata `strupper()`, `strlower()`, `strproper()`, `ustrupper()`, `ustrlower()`, and `ustrtitle()` functions change the case of ASCII and Unicode strings, respectively.

```
clear
input str20 string
"John Smith"
"Jane Cook"
end

generate upper = strupper(string)
generate lower = strlower(string)
generate title = strproper(string)
list
```

The equivalent Python functions are `upper`, `lower`, and `title`.

```
In [35]: firstlast = pd.DataFrame({"string": ["John Smith", "Jane Cook"]})

In [36]: firstlast["upper"] = firstlast["string"].str.upper()

In [37]: firstlast["lower"] = firstlast["string"].str.lower()

In [38]: firstlast["title"] = firstlast["string"].str.title()
```

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```
In [39]: firstlast
Out[39]:
       string       upper       lower       title
0  John Smith  JOHN SMITH  john smith  John Smith
1   Jane Cook   JANE COOK   jane cook   Jane Cook
```

Merging

The following tables will be used in the merge examples

```
In [40]: df1 = pd.DataFrame({"key": ["A", "B", "C", "D"], "value": np.random.randn(4)}
↪)

In [41]: df1
Out[41]:
  key     value
0   A  0.469112
1   B -0.282863
2   C -1.509059
3   D -1.135632

In [42]: df2 = pd.DataFrame({"key": ["B", "D", "D", "E"], "value": np.random.randn(4)}
↪)

In [43]: df2
Out[43]:
  key     value
0   B  1.212112
1   D -0.173215
2   D  0.119209
3   E -1.044236
```

In Stata, to perform a merge, one data set must be in memory and the other must be referenced as a file name on disk. In contrast, Python must have both `DataFrames` already in memory.

By default, Stata performs an outer join, where all observations from both data sets are left in memory after the merge. One can keep only observations from the initial data set, the merged data set, or the intersection of the two by using the values created in the `_merge` variable.

```
* First create df2 and save to disk
clear
input str1 key
B
D
D
E
end
generate value = rnormal()
save df2.dta

* Now create df1 in memory
clear
input str1 key
A
B
```

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```
C
D
end
generate value = rnormal()

preserve

* Left join
merge 1:n key using df2.dta
keep if _merge == 1

* Right join
restore, preserve
merge 1:n key using df2.dta
keep if _merge == 2

* Inner join
restore, preserve
merge 1:n key using df2.dta
keep if _merge == 3

* Outer join
restore
merge 1:n key using df2.dta
```

pandas DataFrames have a *DataFrame.merge()* method, which provides similar functionality. Note that different join types are accomplished via the `how` keyword.

```
In [44]: inner_join = df1.merge(df2, on=["key"], how="inner")

In [45]: inner_join
Out[45]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209

In [46]: left_join = df1.merge(df2, on=["key"], how="left")

In [47]: left_join
Out[47]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209

In [48]: right_join = df1.merge(df2, on=["key"], how="right")

In [49]: right_join
Out[49]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
```

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```
3   E       NaN -1.044236

In [50]: outer_join = df1.merge(df2, on=["key"], how="outer")

In [51]: outer_join
Out[51]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236
```

Missing data

Like Stata, pandas has a representation for missing data – the special float value `NaN` (not a number). Many of the semantics are the same; for example missing data propagates through numeric operations, and is ignored by default for aggregations.

```
In [52]: outer_join
Out[52]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236

In [53]: outer_join["value_x"] + outer_join["value_y"]
Out[53]:
0         NaN
1    0.929249
2         NaN
3   -1.308847
4   -1.016424
5         NaN
dtype: float64

In [54]: outer_join["value_x"].sum()
Out[54]: -3.5940742896293765
```

One difference is that missing data cannot be compared to its sentinel value. For example, in Stata you could do this to filter missing values.

```
* Keep missing values
list if value_x == .
* Keep non-missing values
list if value_x != .
```

This doesn't work in pandas. Instead, the `pd.isna()` or `pd.notna()` functions should be used for comparisons.

```
In [55]: outer_join[pd.isna(outer_join["value_x"])]
Out[55]:
```

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```
  key  value_x   value_y
5   E      NaN -1.044236

In [56]: outer_join[pd.notna(outer_join["value_x"])]
Out[56]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
```

pandas also provides a variety of methods to work with missing data – some of which would be challenging to express in Stata. For example, there are methods to drop all rows with any missing values, replacing missing values with a specified value, like the mean, or forward filling from previous rows. See the *missing data documentation* for more.

```
# Drop rows with any missing value
In [57]: outer_join.dropna()
Out[57]:
  key   value_x   value_y
1   B -0.282863  1.212112
3   D -1.135632 -0.173215
4   D -1.135632  0.119209

# Fill forwards
In [58]: outer_join.fillna(method="ffill")
Out[58]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059  1.212112
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E -1.135632 -1.044236

# Impute missing values with the mean
In [59]: outer_join["value_x"].fillna(outer_join["value_x"].mean())
Out[59]:
0    0.469112
1   -0.282863
2   -1.509059
3   -1.135632
4   -1.135632
5   -0.718815
Name: value_x, dtype: float64
```

GroupBy

Aggregation

Stata's `collapse` can be used to group by one or more key variables and compute aggregations on numeric columns.

```
collapse (sum) total_bill tip, by(sex smoker)
```

pandas provides a flexible `groupby` mechanism that allows similar aggregations. See the *groupby documentation* for more details and examples.

```
In [60]: tips_summed = tips.groupby(["sex", "smoker"])[["total_bill", "tip"]].sum()

In [61]: tips_summed.head()
Out[61]:
               total_bill     tip
sex    smoker
Female No          869.68  149.77
       Yes         527.27   96.74
Male   No         1725.75  302.00
       Yes        1217.07  183.07
```

Transformation

In Stata, if the group aggregations need to be used with the original data set, one would usually use `bysort` with `egen()`. For example, to subtract the mean for each observation by smoker group.

```
bysort sex smoker: egen group_bill = mean(total_bill)
generate adj_total_bill = total_bill - group_bill
```

pandas `groupby` provides a `transform` mechanism that allows these type of operations to be succinctly expressed in one operation.

```
In [62]: gb = tips.groupby("smoker")["total_bill"]

In [63]: tips["adj_total_bill"] = tips["total_bill"] - gb.transform("mean")

In [64]: tips.head()
Out[64]:
     total_bill   tip     sex smoker   day    time  size  adj_total_bill
67         1.07  1.00  Female    Yes   Sat  Dinner     1      -17.686344
92         3.75  1.00  Female    Yes   Fri  Dinner     2      -15.006344
111        5.25  1.00  Female     No   Sat  Dinner     1      -11.938278
145        6.35  1.50  Female     No  Thur   Lunch     2      -10.838278
135        6.51  1.25  Female     No  Thur   Lunch     2      -10.678278
```

By group processing

In addition to aggregation, pandas `groupby` can be used to replicate most other `bysort` processing from Stata. For example, the following example lists the first observation in the current sort order by sex/smoker group.

```
bysort sex smoker: list if _n == 1
```

In pandas this would be written as:

```
In [65]: tips.groupby(["sex", "smoker"]).first()
Out[65]:
               total_bill   tip   day    time  size  adj_total_bill
sex    smoker
Female No            5.25  1.00   Sat  Dinner     1      -11.938278
       Yes           1.07  1.00   Sat  Dinner     1      -17.686344
Male   No            5.51  2.00  Thur   Lunch     2      -11.678278
       Yes           5.25  5.15   Sun  Dinner     2      -13.506344
```

Other considerations

Disk vs memory

pandas and Stata both operate exclusively in memory. This means that the size of data able to be loaded in pandas is limited by your machine's memory. If out of core processing is needed, one possibility is the dask.dataframe library, which provides a subset of pandas functionality for an on-disk `DataFrame`.

1.4.5 Community tutorials

This is a guide to many pandas tutorials by the community, geared mainly for new users.

pandas cookbook by Julia Evans

The goal of this 2015 cookbook (by Julia Evans) is to give you some concrete examples for getting started with pandas. These are examples with real-world data, and all the bugs and weirdness that entails. For the table of contents, see the pandas-cookbook GitHub repository.

Learn pandas by Hernan Rojas

A set of lesson for new pandas users: https://bitbucket.org/hrojas/learn-pandas

Practical data analysis with Python

This guide is an introduction to the data analysis process using the Python data ecosystem and an interesting open dataset. There are four sections covering selected topics as munging data, aggregating data, visualizing data and time series.

Exercises for new users

Practice your skills with real data sets and exercises. For more resources, please visit the main repository.

Modern pandas

Tutorial series written in 2016 by Tom Augspurger. The source may be found in the GitHub repository TomAugspurger/effective-pandas.

- Modern Pandas
- Method Chaining
- Indexes
- Performance
- Tidy Data
- Visualization
- Timeseries

Excel charts with pandas, vincent and xlsxwriter

- Using Pandas and XlsxWriter to create Excel charts

Video tutorials

- Pandas From The Ground Up (2015) (2:24) GitHub repo
- Introduction Into Pandas (2016) (1:28) GitHub repo
- Pandas: .head() to .tail() (2016) (1:26) GitHub repo
- Data analysis in Python with pandas (2016-2018) GitHub repo and Jupyter Notebook
- Best practices with pandas (2018) GitHub repo and Jupyter Notebook

Various tutorials

- Wes McKinney's (pandas BDFL) blog
- Statistical analysis made easy in Python with SciPy and pandas DataFrames, by Randal Olson
- Statistical Data Analysis in Python, tutorial videos, by Christopher Fonnesbeck from SciPy 2013
- Financial analysis in Python, by Thomas Wiecki
- Intro to pandas data structures, by Greg Reda
- Pandas and Python: Top 10, by Manish Amde
- Pandas DataFrames Tutorial, by Karlijn Willems
- A concise tutorial with real life examples

CHAPTER

TWO

USER GUIDE

The User Guide covers all of pandas by topic area. Each of the subsections introduces a topic (such as "working with missing data"), and discusses how pandas approaches the problem, with many examples throughout.

Users brand-new to pandas should start with 10min.

For a high level summary of the pandas fundamentals, see *Intro to data structures* and *Essential basic functionality*.

Further information on any specific method can be obtained in the *API reference*. {{ header }}

2.1 10 minutes to pandas

This is a short introduction to pandas, geared mainly for new users. You can see more complex recipes in the *Cookbook*.

Customarily, we import as follows:

```
In [1]: import numpy as np

In [2]: import pandas as pd
```

2.1.1 Object creation

See the *Data Structure Intro section*.

Creating a `Series` by passing a list of values, letting pandas create a default integer index:

```
In [3]: s = pd.Series([1, 3, 5, np.nan, 6, 8])

In [4]: s
Out[4]:
0    1.0
1    3.0
2    5.0
3    NaN
4    6.0
5    8.0
dtype: float64
```

Creating a `DataFrame` by passing a NumPy array, with a datetime index and labeled columns:

```
In [5]: dates = pd.date_range("20130101", periods=6)

In [6]: dates
```

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```
Out[6]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')

In [7]: df = pd.DataFrame(np.random.randn(6, 4), index=dates, columns=list("ABCD"))

In [8]: df
Out[8]:
                   A         B         C         D
2013-01-01 -0.017395  0.364500  0.302532 -1.302813
2013-01-02  0.005993 -0.158535  0.882132 -0.717757
2013-01-03 -1.524506  1.416665 -0.075971  0.943722
2013-01-04 -0.949638 -2.332449 -0.211477  0.542882
2013-01-05 -1.489077  1.467011 -0.306292  1.136315
2013-01-06  2.382942  0.059217  0.890958  0.942086
```

Creating a `DataFrame` by passing a dict of objects that can be converted to series-like.

```
In [9]: df2 = pd.DataFrame(
   ...:     {
   ...:         "A": 1.0,
   ...:         "B": pd.Timestamp("20130102"),
   ...:         "C": pd.Series(1, index=list(range(4)), dtype="float32"),
   ...:         "D": np.array([3] * 4, dtype="int32"),
   ...:         "E": pd.Categorical(["test", "train", "test", "train"]),
   ...:         "F": "foo",
   ...:     }
   ...: )
   ...:

In [10]: df2
Out[10]:
     A          B    C  D      E    F
0  1.0 2013-01-02  1.0  3   test  foo
1  1.0 2013-01-02  1.0  3  train  foo
2  1.0 2013-01-02  1.0  3   test  foo
3  1.0 2013-01-02  1.0  3  train  foo
```

The columns of the resulting `DataFrame` have different *dtypes*.

```
In [11]: df2.dtypes
Out[11]:
A           float64
B    datetime64[ns]
C           float32
D             int32
E          category
F            object
dtype: object
```

If you're using IPython, tab completion for column names (as well as public attributes) is automatically enabled. Here's a subset of the attributes that will be completed:

```
In [12]: df2.<TAB>  # noqa: E225, E999
df2.A                  df2.bool
```

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```
df2.abs                 df2.boxplot
df2.add                 df2.C
df2.add_prefix          df2.clip
df2.add_suffix          df2.columns
df2.align               df2.copy
df2.all                 df2.count
df2.any                 df2.combine
df2.append              df2.D
df2.apply               df2.describe
df2.applymap            df2.diff
df2.B                   df2.duplicated
```

As you can see, the columns `A`, `B`, `C`, and `D` are automatically tab completed. `E` and `F` are there as well; the rest of the attributes have been truncated for brevity.

2.1.2 Viewing data

See the *Basics section*.

Here is how to view the top and bottom rows of the frame:

```
In [13]: df.head()
Out[13]:
                   A         B         C         D
2013-01-01 -0.017395  0.364500  0.302532 -1.302813
2013-01-02  0.005993 -0.158535  0.882132 -0.717757
2013-01-03 -1.524506  1.416665 -0.075971  0.943722
2013-01-04 -0.949638 -2.332449 -0.211477  0.542882
2013-01-05 -1.489077  1.467011 -0.306292  1.136315

In [14]: df.tail(3)
Out[14]:
                   A         B         C         D
2013-01-04 -0.949638 -2.332449 -0.211477  0.542882
2013-01-05 -1.489077  1.467011 -0.306292  1.136315
2013-01-06  2.382942  0.059217  0.890958  0.942086
```

Display the index, columns:

```
In [15]: df.index
Out[15]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')

In [16]: df.columns
Out[16]: Index(['A', 'B', 'C', 'D'], dtype='object')
```

`DataFrame.to_numpy()` gives a NumPy representation of the underlying data. Note that this can be an expensive operation when your `DataFrame` has columns with different data types, which comes down to a fundamental difference between pandas and NumPy: **NumPy arrays have one dtype for the entire array, while pandas DataFrames have one dtype per column**. When you call `DataFrame.to_numpy()`, pandas will find the NumPy dtype that can hold *all* of the dtypes in the DataFrame. This may end up being `object`, which requires casting every value to a Python object.

For `df`, our `DataFrame` of all floating-point values, `DataFrame.to_numpy()` is fast and doesn't require copying data.

```
In [17]: df.to_numpy()
Out[17]:
array([[-0.01739519,  0.36450034,  0.30253184, -1.30281255],
       [ 0.00599282, -0.15853485,  0.88213178, -0.71775709],
       [-1.524506  ,  1.41666494, -0.07597084,  0.94372163],
       [-0.94963797, -2.33244904, -0.2114768 ,  0.54288187],
       [-1.48907707,  1.46701068, -0.30629243,  1.13631511],
       [ 2.38294167,  0.05921668,  0.89095785,  0.942086  ]])
```

For `df2`, the `DataFrame` with multiple dtypes, `DataFrame.to_numpy()` is relatively expensive.

```
In [18]: df2.to_numpy()
Out[18]:
array([[1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo']],
      dtype=object)
```

Note: `DataFrame.to_numpy()` does *not* include the index or column labels in the output.

`describe()` shows a quick statistic summary of your data:

```
In [19]: df.describe()
Out[19]:
              A         B         C         D
count  6.000000  6.000000  6.000000  6.000000
mean  -0.265280  0.136068  0.246980  0.257406
std    1.462859  1.389229  0.536992  1.017744
min   -1.524506 -2.332449 -0.306292 -1.302813
25%   -1.354217 -0.104097 -0.177600 -0.402597
50%   -0.483517  0.211859  0.113280  0.742484
75%    0.000146  1.153624  0.737232  0.943313
max    2.382942  1.467011  0.890958  1.136315
```

Transposing your data:

```
In [20]: df.T
Out[20]:
   2013-01-01  2013-01-02  2013-01-03  2013-01-04  2013-01-05  2013-01-06
A   -0.017395    0.005993   -1.524506   -0.949638   -1.489077    2.382942
B    0.364500   -0.158535    1.416665   -2.332449    1.467011    0.059217
C    0.302532    0.882132   -0.075971   -0.211477   -0.306292    0.890958
D   -1.302813   -0.717757    0.943722    0.542882    1.136315    0.942086
```

Sorting by an axis:

```
In [21]: df.sort_index(axis=1, ascending=False)
Out[21]:
                   D         C         B         A
2013-01-01 -1.302813  0.302532  0.364500 -0.017395
2013-01-02 -0.717757  0.882132 -0.158535  0.005993
2013-01-03  0.943722 -0.075971  1.416665 -1.524506
```

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```
2013-01-04  0.542882 -0.211477 -2.332449 -0.949638
2013-01-05  1.136315 -0.306292  1.467011 -1.489077
2013-01-06  0.942086  0.890958  0.059217  2.382942
```

Sorting by values:

```
In [22]: df.sort_values(by="B")
Out[22]:
                   A         B         C         D
2013-01-04 -0.949638 -2.332449 -0.211477  0.542882
2013-01-02  0.005993 -0.158535  0.882132 -0.717757
2013-01-06  2.382942  0.059217  0.890958  0.942086
2013-01-01 -0.017395  0.364500  0.302532 -1.302813
2013-01-03 -1.524506  1.416665 -0.075971  0.943722
2013-01-05 -1.489077  1.467011 -0.306292  1.136315
```

2.1.3 Selection

Note: While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods, `.at`, `.iat`, `.loc` and `.iloc`.

See the indexing documentation *Indexing and Selecting Data* and *MultiIndex / Advanced Indexing*.

Getting

Selecting a single column, which yields a `Series`, equivalent to `df.A`:

```
In [23]: df["A"]
Out[23]:
2013-01-01   -0.017395
2013-01-02    0.005993
2013-01-03   -1.524506
2013-01-04   -0.949638
2013-01-05   -1.489077
2013-01-06    2.382942
Freq: D, Name: A, dtype: float64
```

Selecting via `[]`, which slices the rows.

```
In [24]: df[0:3]
Out[24]:
                   A         B         C         D
2013-01-01 -0.017395  0.364500  0.302532 -1.302813
2013-01-02  0.005993 -0.158535  0.882132 -0.717757
2013-01-03 -1.524506  1.416665 -0.075971  0.943722

In [25]: df["20130102":"20130104"]
Out[25]:
                   A         B         C         D
2013-01-02  0.005993 -0.158535  0.882132 -0.717757
```

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```
2013-01-03 -1.524506  1.416665 -0.075971  0.943722
2013-01-04 -0.949638 -2.332449 -0.211477  0.542882
```

Selection by label

See more in *Selection by Label*.

For getting a cross section using a label:

```
In [26]: df.loc[dates[0]]
Out[26]:
A   -0.017395
B    0.364500
C    0.302532
D   -1.302813
Name: 2013-01-01 00:00:00, dtype: float64
```

Selecting on a multi-axis by label:

```
In [27]: df.loc[:, ["A", "B"]]
Out[27]:
                   A         B
2013-01-01 -0.017395  0.364500
2013-01-02  0.005993 -0.158535
2013-01-03 -1.524506  1.416665
2013-01-04 -0.949638 -2.332449
2013-01-05 -1.489077  1.467011
2013-01-06  2.382942  0.059217
```

Showing label slicing, both endpoints are *included*:

```
In [28]: df.loc["20130102":"20130104", ["A", "B"]]
Out[28]:
                   A         B
2013-01-02  0.005993 -0.158535
2013-01-03 -1.524506  1.416665
2013-01-04 -0.949638 -2.332449
```

Reduction in the dimensions of the returned object:

```
In [29]: df.loc["20130102", ["A", "B"]]
Out[29]:
A    0.005993
B   -0.158535
Name: 2013-01-02 00:00:00, dtype: float64
```

For getting a scalar value:

```
In [30]: df.loc[dates[0], "A"]
Out[30]: -0.01739519470348764
```

For getting fast access to a scalar (equivalent to the prior method):

```
In [31]: df.at[dates[0], "A"]
Out[31]: -0.01739519470348764
```

Selection by position

See more in *Selection by Position*.

Select via the position of the passed integers:

```
In [32]: df.iloc[3]
Out[32]:
A   -0.949638
B   -2.332449
C   -0.211477
D    0.542882
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/Python:

```
In [33]: df.iloc[3:5, 0:2]
Out[33]:
                   A         B
2013-01-04 -0.949638 -2.332449
2013-01-05 -1.489077  1.467011
```

By lists of integer position locations, similar to the NumPy/Python style:

```
In [34]: df.iloc[[1, 2, 4], [0, 2]]
Out[34]:
                   A         C
2013-01-02  0.005993  0.882132
2013-01-03 -1.524506 -0.075971
2013-01-05 -1.489077 -0.306292
```

For slicing rows explicitly:

```
In [35]: df.iloc[1:3, :]
Out[35]:
                   A         B         C         D
2013-01-02  0.005993 -0.158535  0.882132 -0.717757
2013-01-03 -1.524506  1.416665 -0.075971  0.943722
```

For slicing columns explicitly:

```
In [36]: df.iloc[:, 1:3]
Out[36]:
                   B         C
2013-01-01  0.364500  0.302532
2013-01-02 -0.158535  0.882132
2013-01-03  1.416665 -0.075971
2013-01-04 -2.332449 -0.211477
2013-01-05  1.467011 -0.306292
2013-01-06  0.059217  0.890958
```

For getting a value explicitly:

```
In [37]: df.iloc[1, 1]
Out[37]: -0.1585348456677451
```

For getting fast access to a scalar (equivalent to the prior method):

```
In [38]: df.iat[1, 1]
Out[38]: -0.1585348456677451
```

Boolean indexing

Using a single column's values to select data.

```
In [39]: df[df["A"] > 0]
Out[39]:
                   A         B         C         D
2013-01-02  0.005993 -0.158535  0.882132 -0.717757
2013-01-06  2.382942  0.059217  0.890958  0.942086
```

Selecting values from a DataFrame where a boolean condition is met.

```
In [40]: df[df > 0]
Out[40]:
                   A         B         C         D
2013-01-01       NaN  0.364500  0.302532       NaN
2013-01-02  0.005993       NaN  0.882132       NaN
2013-01-03       NaN  1.416665       NaN  0.943722
2013-01-04       NaN       NaN       NaN  0.542882
2013-01-05       NaN  1.467011       NaN  1.136315
2013-01-06  2.382942  0.059217  0.890958  0.942086
```

Using the `isin()` method for filtering:

```
In [41]: df2 = df.copy()

In [42]: df2["E"] = ["one", "one", "two", "three", "four", "three"]

In [43]: df2
Out[43]:
                   A         B         C         D      E
2013-01-01 -0.017395  0.364500  0.302532 -1.302813    one
2013-01-02  0.005993 -0.158535  0.882132 -0.717757    one
2013-01-03 -1.524506  1.416665 -0.075971  0.943722    two
2013-01-04 -0.949638 -2.332449 -0.211477  0.542882  three
2013-01-05 -1.489077  1.467011 -0.306292  1.136315   four
2013-01-06  2.382942  0.059217  0.890958  0.942086  three

In [44]: df2[df2["E"].isin(["two", "four"])]
Out[44]:
                   A         B         C         D     E
2013-01-03 -1.524506  1.416665 -0.075971  0.943722   two
2013-01-05 -1.489077  1.467011 -0.306292  1.136315  four
```

Setting

Setting a new column automatically aligns the data by the indexes.

```
In [45]: s1 = pd.Series([1, 2, 3, 4, 5, 6], index=pd.date_range("20130102",␣
↪periods=6))

In [46]: s1
Out[46]:
2013-01-02    1
2013-01-03    2
2013-01-04    3
2013-01-05    4
2013-01-06    5
2013-01-07    6
Freq: D, dtype: int64

In [47]: df["F"] = s1
```

Setting values by label:

```
In [48]: df.at[dates[0], "A"] = 0
```

Setting values by position:

```
In [49]: df.iat[0, 1] = 0
```

Setting by assigning with a NumPy array:

```
In [50]: df.loc[:, "D"] = np.array([5] * len(df))
```

The result of the prior setting operations.

```
In [51]: df
Out[51]:
                   A         B         C  D    F
2013-01-01  0.000000  0.000000  0.302532  5  NaN
2013-01-02  0.005993 -0.158535  0.882132  5  1.0
2013-01-03 -1.524506  1.416665 -0.075971  5  2.0
2013-01-04 -0.949638 -2.332449 -0.211477  5  3.0
2013-01-05 -1.489077  1.467011 -0.306292  5  4.0
2013-01-06  2.382942  0.059217  0.890958  5  5.0
```

A `where` operation with setting.

```
In [52]: df2 = df.copy()

In [53]: df2[df2 > 0] = -df2

In [54]: df2
Out[54]:
                   A         B         C  D    F
2013-01-01  0.000000  0.000000 -0.302532 -5  NaN
2013-01-02 -0.005993 -0.158535 -0.882132 -5 -1.0
2013-01-03 -1.524506 -1.416665 -0.075971 -5 -2.0
2013-01-04 -0.949638 -2.332449 -0.211477 -5 -3.0
2013-01-05 -1.489077 -1.467011 -0.306292 -5 -4.0
2013-01-06 -2.382942 -0.059217 -0.890958 -5 -5.0
```

2.1.4 Missing data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the *Missing Data section*.

Reindexing allows you to change/add/delete the index on a specified axis. This returns a copy of the data.

```
In [55]: df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ["E"])

In [56]: df1.loc[dates[0] : dates[1], "E"] = 1

In [57]: df1
Out[57]:
                   A         B         C  D    F    E
2013-01-01  0.000000  0.000000  0.302532  5  NaN  1.0
2013-01-02  0.005993 -0.158535  0.882132  5  1.0  1.0
2013-01-03 -1.524506  1.416665 -0.075971  5  2.0  NaN
2013-01-04 -0.949638 -2.332449 -0.211477  5  3.0  NaN
```

To drop any rows that have missing data.

```
In [58]: df1.dropna(how="any")
Out[58]:
                   A         B         C  D    F    E
2013-01-02  0.005993 -0.158535  0.882132  5  1.0  1.0
```

Filling missing data.

```
In [59]: df1.fillna(value=5)
Out[59]:
                   A         B         C  D    F    E
2013-01-01  0.000000  0.000000  0.302532  5  5.0  1.0
2013-01-02  0.005993 -0.158535  0.882132  5  1.0  1.0
2013-01-03 -1.524506  1.416665 -0.075971  5  2.0  5.0
2013-01-04 -0.949638 -2.332449 -0.211477  5  3.0  5.0
```

To get the boolean mask where values are `nan`.

```
In [60]: pd.isna(df1)
Out[60]:
                A      B      C      D      F      E
2013-01-01  False  False  False  False   True  False
2013-01-02  False  False  False  False  False  False
2013-01-03  False  False  False  False  False   True
2013-01-04  False  False  False  False  False   True
```

2.1.5 Operations

See the *Basic section on Binary Ops*.

Stats

Operations in general *exclude* missing data.

Performing a descriptive statistic:

```
In [61]: df.mean()
Out[61]:
A   -0.262381
B    0.075318
C    0.246980
D    5.000000
F    3.000000
dtype: float64
```

Same operation on the other axis:

```
In [62]: df.mean(1)
Out[62]:
2013-01-01    1.325633
2013-01-02    1.345918
2013-01-03    1.363238
2013-01-04    0.901287
2013-01-05    1.734328
2013-01-06    2.666623
Freq: D, dtype: float64
```

Operating with objects that have different dimensionality and need alignment. In addition, pandas automatically broadcasts along the specified dimension.

```
In [63]: s = pd.Series([1, 3, 5, np.nan, 6, 8], index=dates).shift(2)

In [64]: s
Out[64]:
2013-01-01    NaN
2013-01-02    NaN
2013-01-03    1.0
2013-01-04    3.0
2013-01-05    5.0
2013-01-06    NaN
Freq: D, dtype: float64

In [65]: df.sub(s, axis="index")
Out[65]:
                   A         B         C    D    F
2013-01-01       NaN       NaN       NaN  NaN  NaN
2013-01-02       NaN       NaN       NaN  NaN  NaN
2013-01-03 -2.524506  0.416665 -1.075971  4.0  1.0
2013-01-04 -3.949638 -5.332449 -3.211477  2.0  0.0
2013-01-05 -6.489077 -3.532989 -5.306292  0.0 -1.0
2013-01-06       NaN       NaN       NaN  NaN  NaN
```

Apply

Applying functions to the data:

```
In [66]: df.apply(np.cumsum)
Out[66]:
                   A         B         C   D     F
2013-01-01  0.000000  0.000000  0.302532   5   NaN
2013-01-02  0.005993 -0.158535  1.184664  10   1.0
2013-01-03 -1.518513  1.258130  1.108693  15   3.0
2013-01-04 -2.468151 -1.074319  0.897216  20   6.0
2013-01-05 -3.957228  0.392692  0.590924  25  10.0
2013-01-06 -1.574287  0.451908  1.481881  30  15.0

In [67]: df.apply(lambda x: x.max() - x.min())
Out[67]:
A    3.907448
B    3.799460
C    1.197250
D    0.000000
F    4.000000
dtype: float64
```

Histogramming

See more at *Histogramming and Discretization*.

```
In [68]: s = pd.Series(np.random.randint(0, 7, size=10))

In [69]: s
Out[69]:
0    0
1    0
2    5
3    1
4    6
5    6
6    3
7    3
8    2
9    2
dtype: int64

In [70]: s.value_counts()
Out[70]:
0    2
2    2
3    2
6    2
1    1
5    1
dtype: int64
```

String Methods

Series is equipped with a set of string processing methods in the `str` attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in `str` generally uses regular expressions by default (and in some cases always uses them). See more at *Vectorized String Methods*.

```
In [71]: s = pd.Series(["A", "B", "C", "Aaba", "Baca", np.nan, "CABA", "dog", "cat"])

In [72]: s.str.lower()
Out[72]:
0       a
1       b
2       c
3    aaba
4    baca
5     NaN
6    caba
7     dog
8     cat
dtype: object
```

2.1.6 Merge

Concat

pandas provides various facilities for easily combining together Series and DataFrame objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

See the *Merging section*.

Concatenating pandas objects together with `concat()`:

```
In [73]: df = pd.DataFrame(np.random.randn(10, 4))

In [74]: df
Out[74]:
          0         1         2         3
0 -0.304882  1.757218  0.596583 -0.946131
1  0.691143 -2.132880 -0.505485  3.283012
2  1.216023 -1.064367 -1.278912  0.658968
3 -0.007922 -0.304560  0.877514  0.964475
4 -0.424134 -1.047107 -0.699683 -0.427298
5 -1.713227 -0.191534  1.041079  0.290495
6 -0.205061 -0.049839 -1.105258 -1.440386
7 -0.366011  0.668819  1.231796 -1.113485
8 -0.818822  0.203953  0.827694 -2.094117
9  0.264517  0.095371  1.118650 -1.424047

# break it into pieces
In [75]: pieces = [df[:3], df[3:7], df[7:]]

In [76]: pd.concat(pieces)
Out[76]:
          0         1         2         3
0 -0.304882  1.757218  0.596583 -0.946131
1  0.691143 -2.132880 -0.505485  3.283012
```

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```
2  1.216023 -1.064367 -1.278912  0.658968
3 -0.007922 -0.304560  0.877514  0.964475
4 -0.424134 -1.047107 -0.699683 -0.427298
5 -1.713227 -0.191534  1.041079  0.290495
6 -0.205061 -0.049839 -1.105258 -1.440386
7 -0.366011  0.668819  1.231796 -1.113485
8 -0.818822  0.203953  0.827694 -2.094117
9  0.264517  0.095371  1.118650 -1.424047
```

Note: Adding a column to a `DataFrame` is relatively fast. However, adding a row requires a copy, and may be expensive. We recommend passing a pre-built list of records to the `DataFrame` constructor instead of building a `DataFrame` by iteratively appending records to it. See *Appending to dataframe* for more.

Join

SQL style merges. See the *Database style joining* section.

```
In [77]: left = pd.DataFrame({"key": ["foo", "foo"], "lval": [1, 2]})

In [78]: right = pd.DataFrame({"key": ["foo", "foo"], "rval": [4, 5]})

In [79]: left
Out[79]:
   key  lval
0  foo     1
1  foo     2

In [80]: right
Out[80]:
   key  rval
0  foo     4
1  foo     5

In [81]: pd.merge(left, right, on="key")
Out[81]:
   key  lval  rval
0  foo     1     4
1  foo     1     5
2  foo     2     4
3  foo     2     5
```

Another example that can be given is:

```
In [82]: left = pd.DataFrame({"key": ["foo", "bar"], "lval": [1, 2]})

In [83]: right = pd.DataFrame({"key": ["foo", "bar"], "rval": [4, 5]})

In [84]: left
Out[84]:
   key  lval
0  foo     1
1  bar     2
```

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```
In [85]: right
Out[85]:
   key  rval
0  foo     4
1  bar     5

In [86]: pd.merge(left, right, on="key")
Out[86]:
   key  lval  rval
0  foo     1     4
1  bar     2     5
```

2.1.7 Grouping

By "group by" we are referring to a process involving one or more of the following steps:

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

See the *Grouping section*.

```
In [87]: df = pd.DataFrame(
   ....:     {
   ....:         "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],
   ....:         "B": ["one", "one", "two", "three", "two", "two", "one", "three"],
   ....:         "C": np.random.randn(8),
   ....:         "D": np.random.randn(8),
   ....:     }
   ....: )
   ....:

In [88]: df
Out[88]:
     A      B         C         D
0  foo    one  0.005256  1.451797
1  bar    one -0.890238 -0.355059
2  foo    two -0.172158  0.178008
3  bar  three -0.238385 -0.329206
4  foo    two -1.298970  0.759589
5  bar    two -0.091263 -1.224087
6  foo    one  0.569348  0.218606
7  foo  three -0.372033  0.379886
```

Grouping and then applying the `sum()` function to the resulting groups.

```
In [89]: df.groupby("A").sum()
Out[89]:
            C         D
A
bar -1.219885 -1.908352
foo -1.268556  2.987886
```

Grouping by multiple columns forms a hierarchical index, and again we can apply the `sum()` function.

```
In [90]: df.groupby(["A", "B"]).sum()
Out[90]:
                  C         D
A   B
bar one   -0.890238 -0.355059
    three -0.238385 -0.329206
    two   -0.091263 -1.224087
foo one    0.574604  1.670403
    three -0.372033  0.379886
    two   -1.471128  0.937597
```

2.1.8 Reshaping

See the sections on *Hierarchical Indexing* and *Reshaping*.

Stack

```
In [91]: tuples = list(
   ....:     zip(
   ....:         *[
   ....:             ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
   ....:             ["one", "two", "one", "two", "one", "two", "one", "two"],
   ....:         ]
   ....:     )
   ....: )
   ....:

In [92]: index = pd.MultiIndex.from_tuples(tuples, names=["first", "second"])

In [93]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=["A", "B"])

In [94]: df2 = df[:4]

In [95]: df2
Out[95]:
                     A         B
first second
bar   one    -0.642542 -0.743288
      two     0.291241  0.341981
baz   one     0.357798  0.137430
      two    -1.248219 -1.269893
```

The `stack()` method "compresses" a level in the DataFrame's columns.

```
In [96]: stacked = df2.stack()

In [97]: stacked
Out[97]:
first  second
bar    one     A   -0.642542
               B   -0.743288
       two     A    0.291241
               B    0.341981
baz    one     A    0.357798
```

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```
               B    0.137430
       two     A   -1.248219
               B   -1.269893
dtype: float64
```

With a "stacked" DataFrame or Series (having a `MultiIndex` as the `index`), the inverse operation of `stack()` is `unstack()`, which by default unstacks the **last level**:

```
In [98]: stacked.unstack()
Out[98]:
                     A         B
first second
bar   one    -0.642542 -0.743288
      two     0.291241  0.341981
baz   one     0.357798  0.137430
      two    -1.248219 -1.269893

In [99]: stacked.unstack(1)
Out[99]:
second        one       two
first
bar   A -0.642542  0.291241
      B -0.743288  0.341981
baz   A  0.357798 -1.248219
      B  0.137430 -1.269893

In [100]: stacked.unstack(0)
Out[100]:
first          bar       baz
second
one    A -0.642542  0.357798
       B -0.743288  0.137430
two    A  0.291241 -1.248219
       B  0.341981 -1.269893
```

Pivot tables

See the section on *Pivot Tables*.

```
In [101]: df = pd.DataFrame(
   .....:     {
   .....:         "A": ["one", "one", "two", "three"] * 3,
   .....:         "B": ["A", "B", "C"] * 4,
   .....:         "C": ["foo", "foo", "foo", "bar", "bar", "bar"] * 2,
   .....:         "D": np.random.randn(12),
   .....:         "E": np.random.randn(12),
   .....:     }
   .....: )
   .....:

In [102]: df
Out[102]:
        A  B    C         D         E
0     one  A  foo -0.264304 -1.544941
1     one  B  foo  1.303494  0.416320
```

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```
2     two  C  foo  1.585765 -0.856392
3   three  A  bar  1.730229 -0.700004
4     one  B  bar -0.945902  0.297704
5     one  C  bar -0.503634  1.297004
6     two  A  foo -0.347961 -0.332132
7   three  B  foo  1.427819  1.149793
8     one  C  foo -1.688035 -0.463522
9     one  A  bar -0.589194 -1.227306
10    two  B  bar -2.169072 -1.396396
11  three  C  bar  0.480584  0.497888
```

We can produce pivot tables from this data very easily:

```
In [103]: pd.pivot_table(df, values="D", index=["A", "B"], columns=["C"])
Out[103]:
C             bar       foo
A     B
one   A -0.589194 -0.264304
      B -0.945902  1.303494
      C -0.503634 -1.688035
three A  1.730229       NaN
      B       NaN  1.427819
      C  0.480584       NaN
two   A       NaN -0.347961
      B -2.169072       NaN
      C       NaN  1.585765
```

2.1.9 Time series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications. See the *Time Series section*.

```
In [104]: rng = pd.date_range("1/1/2012", periods=100, freq="S")

In [105]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [106]: ts.resample("5Min").sum()
Out[106]:
2012-01-01    24704
Freq: 5T, dtype: int64
```

Time zone representation:

```
In [107]: rng = pd.date_range("3/6/2012 00:00", periods=5, freq="D")

In [108]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [109]: ts
Out[109]:
2012-03-06   -0.534235
2012-03-07    0.090111
2012-03-08   -0.510360
2012-03-09    0.738006
2012-03-10    0.366125
```

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```
Freq: D, dtype: float64

In [110]: ts_utc = ts.tz_localize("UTC")

In [111]: ts_utc
Out[111]:
2012-03-06 00:00:00+00:00   -0.534235
2012-03-07 00:00:00+00:00    0.090111
2012-03-08 00:00:00+00:00   -0.510360
2012-03-09 00:00:00+00:00    0.738006
2012-03-10 00:00:00+00:00    0.366125
Freq: D, dtype: float64
```

Converting to another time zone:

```
In [112]: ts_utc.tz_convert("US/Eastern")
Out[112]:
2012-03-05 19:00:00-05:00   -0.534235
2012-03-06 19:00:00-05:00    0.090111
2012-03-07 19:00:00-05:00   -0.510360
2012-03-08 19:00:00-05:00    0.738006
2012-03-09 19:00:00-05:00    0.366125
Freq: D, dtype: float64
```

Converting between time span representations:

```
In [113]: rng = pd.date_range("1/1/2012", periods=5, freq="M")

In [114]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [115]: ts
Out[115]:
2012-01-31    0.314259
2012-02-29   -1.133461
2012-03-31   -0.281168
2012-04-30   -2.552610
2012-05-31   -0.632291
Freq: M, dtype: float64

In [116]: ps = ts.to_period()

In [117]: ps
Out[117]:
2012-01    0.314259
2012-02   -1.133461
2012-03   -0.281168
2012-04   -2.552610
2012-05   -0.632291
Freq: M, dtype: float64

In [118]: ps.to_timestamp()
Out[118]:
2012-01-01    0.314259
2012-02-01   -1.133461
2012-03-01   -0.281168
2012-04-01   -2.552610
2012-05-01   -0.632291
```

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```
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```
In [119]: prng = pd.period_range("1990Q1", "2000Q4", freq="Q-NOV")

In [120]: ts = pd.Series(np.random.randn(len(prng)), prng)

In [121]: ts.index = (prng.asfreq("M", "e") + 1).asfreq("H", "s") + 9

In [122]: ts.head()
Out[122]:
1990-03-01 09:00    0.839129
1990-06-01 09:00   -0.402514
1990-09-01 09:00    0.417724
1990-12-01 09:00   -0.415669
1991-03-01 09:00    0.613872
Freq: H, dtype: float64
```

2.1.10 Categoricals

pandas can include categorical data in a `DataFrame`. For full docs, see the *categorical introduction* and the *API documentation*.

```
In [123]: df = pd.DataFrame(
   .....:     {"id": [1, 2, 3, 4, 5, 6], "raw_grade": ["a", "b", "b", "a", "a", "e"]}
   .....: )
   .....:
```

Convert the raw grades to a categorical data type.

```
In [124]: df["grade"] = df["raw_grade"].astype("category")

In [125]: df["grade"]
Out[125]:
0    a
1    b
2    b
3    a
4    a
5    e
Name: grade, dtype: category
Categories (3, object): ['a', 'b', 'e']
```

Rename the categories to more meaningful names (assigning to `Series.cat.categories()` is in place!).

```
In [126]: df["grade"].cat.categories = ["very good", "good", "very bad"]
```

Reorder the categories and simultaneously add the missing categories (methods under `Series.cat()` return a new `Series` by default).

```
In [127]: df["grade"] = df["grade"].cat.set_categories(
   .....:     ["very bad", "bad", "medium", "good", "very good"]
   .....: )
   .....:

In [128]: df["grade"]
Out[128]:
0    very good
1         good
2         good
3    very good
4    very good
5     very bad
Name: grade, dtype: category
Categories (5, object): ['very bad', 'bad', 'medium', 'good', 'very good']
```

Sorting is per order in the categories, not lexical order.

```
In [129]: df.sort_values(by="grade")
Out[129]:
   id raw_grade      grade
5   6         e   very bad
1   2         b       good
2   3         b       good
0   1         a  very good
3   4         a  very good
4   5         a  very good
```

Grouping by a categorical column also shows empty categories.

```
In [130]: df.groupby("grade").size()
Out[130]:
grade
very bad     1
bad          0
medium       0
good         2
very good    3
dtype: int64
```

2.1.11 Plotting

See the *Plotting* docs.

We use the standard convention for referencing the matplotlib API:

```
In [131]: import matplotlib.pyplot as plt

In [132]: plt.close("all")
```

```
In [133]: ts = pd.Series(np.random.randn(1000), index=pd.date_range("1/1/2000",␣
↪periods=1000))

In [134]: ts = ts.cumsum()
```

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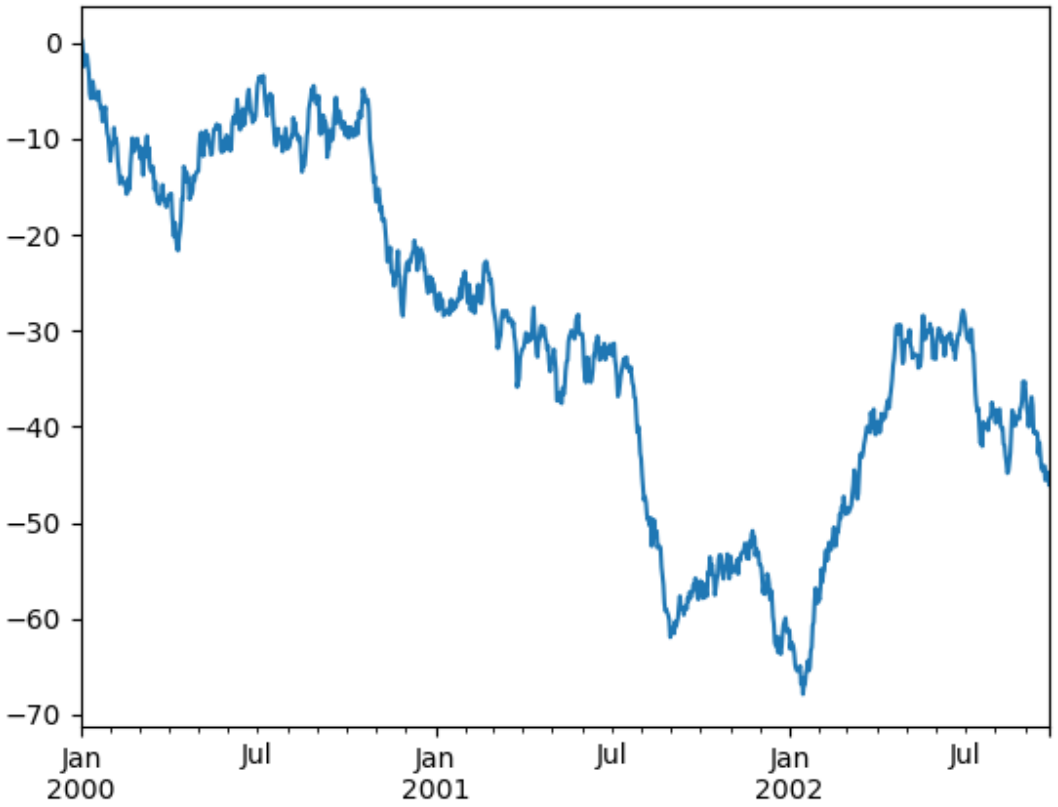
```
In [135]: ts.plot()
Out[135]: <AxesSubplot:>
```



On a DataFrame, the `plot()` method is a convenience to plot all of the columns with labels:

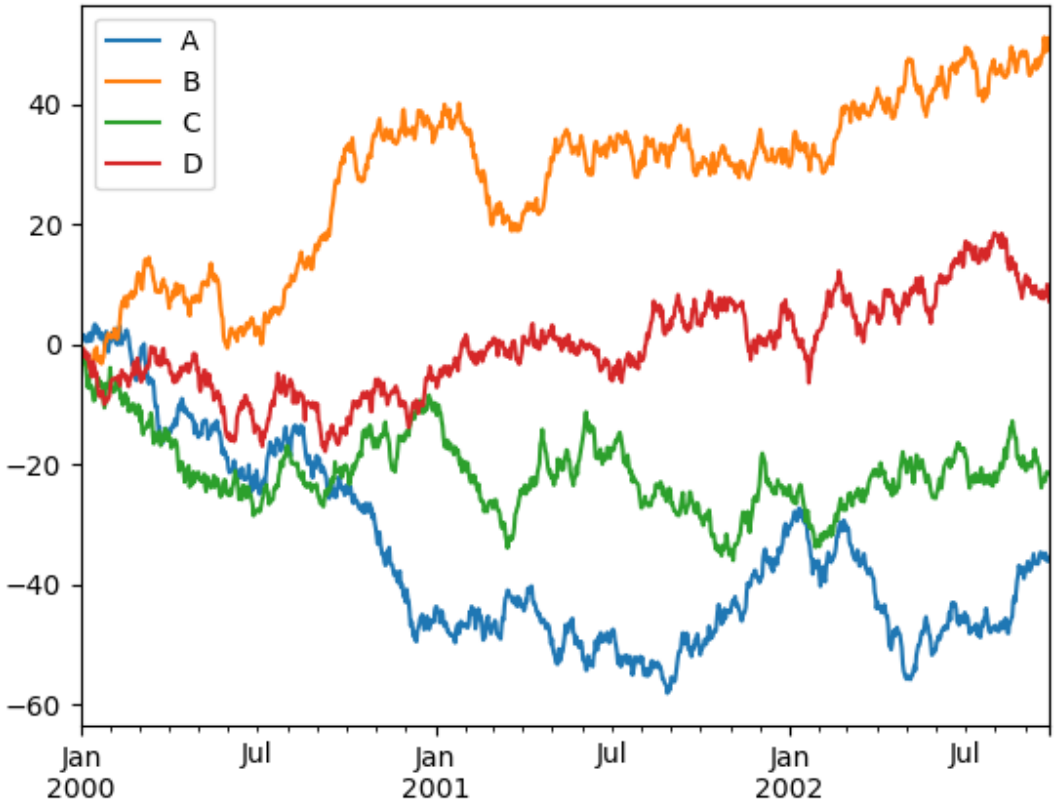
```
In [136]: df = pd.DataFrame(
   .....:     np.random.randn(1000, 4), index=ts.index, columns=["A", "B", "C", "D"]
   .....: )
   .....:

In [137]: df = df.cumsum()

In [138]: plt.figure()
Out[138]: <Figure size 640x480 with 0 Axes>

In [139]: df.plot()
Out[139]: <AxesSubplot:>

In [140]: plt.legend(loc='best')
Out[140]: <matplotlib.legend.Legend at 0x7f259cc0ca00>
```



2.1.12 Getting data in/out

CSV

Writing to a csv file.

```
In [141]: df.to_csv("foo.csv")
```

Reading from a csv file.

```
In [142]: pd.read_csv("foo.csv")
Out[142]:
     Unnamed: 0          A         B          C         D
0    2000-01-01  -1.186158 -0.078953  -0.908334 -0.207319
1    2000-01-02  -0.836655  1.321336   0.381757 -0.114197
2    2000-01-03   0.348941  1.293196  -0.261434 -0.547857
3    2000-01-04  -0.739898  0.689293   0.711139  0.029234
4    2000-01-05  -1.026673  0.012239   0.166625  0.399639
..          ...        ...       ...        ...       ...
995  2002-09-22  39.521172 -7.087277  43.927594 -2.040979
996  2002-09-23  37.651842 -7.828622  43.667711 -1.094352
997  2002-09-24  37.883039 -8.230461  42.401759 -1.030950
998  2002-09-25  38.252827 -7.670058  43.586608 -0.086283
```

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```
999  2002-09-26  36.683986 -8.307952  44.843630 -1.041201

[1000 rows x 5 columns]
```

HDF5

Reading and writing to *HDFStores*.

Writing to a HDF5 Store.

```
In [143]: df.to_hdf("foo.h5", "df")
```

Reading from a HDF5 Store.

```
In [144]: pd.read_hdf("foo.h5", "df")
Out[144]:
                    A         B          C         D
2000-01-01  -1.186158 -0.078953  -0.908334 -0.207319
2000-01-02  -0.836655  1.321336   0.381757 -0.114197
2000-01-03   0.348941  1.293196  -0.261434 -0.547857
2000-01-04  -0.739898  0.689293   0.711139  0.029234
2000-01-05  -1.026673  0.012239   0.166625  0.399639
...               ...       ...        ...       ...
2002-09-22  39.521172 -7.087277  43.927594 -2.040979
2002-09-23  37.651842 -7.828622  43.667711 -1.094352
2002-09-24  37.883039 -8.230461  42.401759 -1.030950
2002-09-25  38.252827 -7.670058  43.586608 -0.086283
2002-09-26  36.683986 -8.307952  44.843630 -1.041201

[1000 rows x 4 columns]
```

Excel

Reading and writing to *MS Excel*.

Writing to an excel file.

```
In [145]: df.to_excel("foo.xlsx", sheet_name="Sheet1")
```

Reading from an excel file.

```
In [146]: pd.read_excel("foo.xlsx", "Sheet1", index_col=None, na_values=["NA"])
Out[146]:
    Unnamed: 0          A         B          C         D
0   2000-01-01  -1.186158 -0.078953  -0.908334 -0.207319
1   2000-01-02  -0.836655  1.321336   0.381757 -0.114197
2   2000-01-03   0.348941  1.293196  -0.261434 -0.547857
3   2000-01-04  -0.739898  0.689293   0.711139  0.029234
4   2000-01-05  -1.026673  0.012239   0.166625  0.399639
..         ...         ...       ...        ...       ...
995 2002-09-22  39.521172 -7.087277  43.927594 -2.040979
996 2002-09-23  37.651842 -7.828622  43.667711 -1.094352
997 2002-09-24  37.883039 -8.230461  42.401759 -1.030950
998 2002-09-25  38.252827 -7.670058  43.586608 -0.086283
```

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```
999 2002-09-26  36.683986 -8.307952  44.843630 -1.041201

[1000 rows x 5 columns]
```

2.1.13 Gotchas

If you are attempting to perform an operation you might see an exception like:

```
>>> if pd.Series([False, True, False]):
...     print("I was true")
Traceback
    ...
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

See *Comparisons* for an explanation and what to do.

See *Gotchas* as well.

2.2 Intro to data structures

We'll start with a quick, non-comprehensive overview of the fundamental data structures in pandas to get you started. The fundamental behavior about data types, indexing, and axis labeling / alignment apply across all of the objects. To get started, import NumPy and load pandas into your namespace:

```
In [1]: import numpy as np

In [2]: import pandas as pd
```

Here is a basic tenet to keep in mind: **data alignment is intrinsic**. The link between labels and data will not be broken unless done so explicitly by you.

We'll give a brief intro to the data structures, then consider all of the broad categories of functionality and methods in separate sections.

2.2.1 Series

Series is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the **index**. The basic method to create a Series is to call:

```
>>> s = pd.Series(data, index=index)
```

Here, `data` can be many different things:

- a Python dict
- an ndarray
- a scalar value (like 5)

The passed **index** is a list of axis labels. Thus, this separates into a few cases depending on what **data is**:

From ndarray

If `data` is an ndarray, **index** must be the same length as **data**. If no index is passed, one will be created having values `[0, ..., len(data) - 1]`.

```
In [3]: s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])

In [4]: s
Out[4]:
a    0.469112
b   -0.282863
c   -1.509059
d   -1.135632
e    1.212112
dtype: float64

In [5]: s.index
Out[5]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

In [6]: pd.Series(np.random.randn(5))
Out[6]:
0   -0.173215
1    0.119209
2   -1.044236
3   -0.861849
4   -2.104569
dtype: float64
```

Note: pandas supports non-unique index values. If an operation that does not support duplicate index values is attempted, an exception will be raised at that time. The reason for being lazy is nearly all performance-based (there are many instances in computations, like parts of GroupBy, where the index is not used).

From dict

Series can be instantiated from dicts:

```
In [7]: d = {"b": 1, "a": 0, "c": 2}

In [8]: pd.Series(d)
Out[8]:
b    1
a    0
c    2
dtype: int64
```

Note: When the data is a dict, and an index is not passed, the `Series` index will be ordered by the dict's insertion order, if you're using Python version >= 3.6 and pandas version >= 0.23.

If you're using Python < 3.6 or pandas < 0.23, and an index is not passed, the `Series` index will be the lexically ordered list of dict keys.

In the example above, if you were on a Python version lower than 3.6 or a pandas version lower than 0.23, the `Series` would be ordered by the lexical order of the dict keys (i.e. `['a', 'b', 'c']` rather than `['b', 'a', 'c']`).

If an index is passed, the values in data corresponding to the labels in the index will be pulled out.

```
In [9]: d = {"a": 0.0, "b": 1.0, "c": 2.0}

In [10]: pd.Series(d)
Out[10]:
a    0.0
b    1.0
c    2.0
dtype: float64

In [11]: pd.Series(d, index=["b", "c", "d", "a"])
Out[11]:
b    1.0
c    2.0
d    NaN
a    0.0
dtype: float64
```

Note: NaN (not a number) is the standard missing data marker used in pandas.

From scalar value

If `data` is a scalar value, an index must be provided. The value will be repeated to match the length of **index**.

```
In [12]: pd.Series(5.0, index=["a", "b", "c", "d", "e"])
Out[12]:
a    5.0
b    5.0
c    5.0
d    5.0
e    5.0
dtype: float64
```

Series is ndarray-like

`Series` acts very similarly to a `ndarray`, and is a valid argument to most NumPy functions. However, operations such as slicing will also slice the index.

```
In [13]: s[0]
Out[13]: 0.4691122999071863

In [14]: s[:3]
Out[14]:
a    0.469112
b   -0.282863
c   -1.509059
dtype: float64

In [15]: s[s > s.median()]
Out[15]:
a    0.469112
e    1.212112
dtype: float64

In [16]: s[[4, 3, 1]]
```

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```
Out[16]:
e    1.212112
d   -1.135632
b   -0.282863
dtype: float64

In [17]: np.exp(s)
Out[17]:
a    1.598575
b    0.753623
c    0.221118
d    0.321219
e    3.360575
dtype: float64
```

Note: We will address array-based indexing like `s[[4, 3, 1]]` in *section*.

Like a NumPy array, a pandas Series has a *dtype*.

```
In [18]: s.dtype
Out[18]: dtype('float64')
```

This is often a NumPy dtype. However, pandas and 3rd-party libraries extend NumPy's type system in a few places, in which case the dtype would be an *ExtensionDtype*. Some examples within pandas are *Categorical data* and *Nullable integer data type*. See *dtypes* for more.

If you need the actual array backing a `Series`, use *Series.array*.

```
In [19]: s.array
Out[19]:
<PandasArray>
[ 0.4691122999071863, -0.2828633443286633, -1.5090585031735124,
 -1.1356323710171934,  1.2121120250208506]
Length: 5, dtype: float64
```

Accessing the array can be useful when you need to do some operation without the index (to disable *automatic alignment*, for example).

Series.array will always be an *ExtensionArray*. Briefly, an ExtensionArray is a thin wrapper around one or more *concrete* arrays like a `numpy.ndarray`. pandas knows how to take an `ExtensionArray` and store it in a `Series` or a column of a `DataFrame`. See *dtypes* for more.

While Series is ndarray-like, if you need an *actual* ndarray, then use *Series.to_numpy()*.

```
In [20]: s.to_numpy()
Out[20]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])
```

Even if the Series is backed by a *ExtensionArray*, *Series.to_numpy()* will return a NumPy ndarray.

Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```
In [21]: s["a"]
Out[21]: 0.4691122999071863

In [22]: s["e"] = 12.0

In [23]: s
Out[23]:
a     0.469112
b    -0.282863
c    -1.509059
d    -1.135632
e    12.000000
dtype: float64

In [24]: "e" in s
Out[24]: True

In [25]: "f" in s
Out[25]: False
```

If a label is not contained, an exception is raised:

```
>>> s["f"]
KeyError: 'f'
```

Using the `get` method, a missing label will return None or specified default:

```
In [26]: s.get("f")

In [27]: s.get("f", np.nan)
Out[27]: nan
```

See also the *section on attribute access*.

Vectorized operations and label alignment with Series

When working with raw NumPy arrays, looping through value-by-value is usually not necessary. The same is true when working with Series in pandas. Series can also be passed into most NumPy methods expecting an ndarray.

```
In [28]: s + s
Out[28]:
a     0.938225
b    -0.565727
c    -3.018117
d    -2.271265
e    24.000000
dtype: float64

In [29]: s * 2
Out[29]:
a     0.938225
b    -0.565727
```

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```
c    -3.018117
d    -2.271265
e    24.000000
dtype: float64

In [30]: np.exp(s)
Out[30]:
a          1.598575
b          0.753623
c          0.221118
d          0.321219
e     162754.791419
dtype: float64
```

A key difference between Series and ndarray is that operations between Series automatically align the data based on label. Thus, you can write computations without giving consideration to whether the Series involved have the same labels.

```
In [31]: s[1:] + s[:-1]
Out[31]:
a          NaN
b    -0.565727
c    -3.018117
d    -2.271265
e          NaN
dtype: float64
```

The result of an operation between unaligned Series will have the **union** of the indexes involved. If a label is not found in one Series or the other, the result will be marked as missing `NaN`. Being able to write code without doing any explicit data alignment grants immense freedom and flexibility in interactive data analysis and research. The integrated data alignment features of the pandas data structures set pandas apart from the majority of related tools for working with labeled data.

Note: In general, we chose to make the default result of operations between differently indexed objects yield the **union** of the indexes in order to avoid loss of information. Having an index label, though the data is missing, is typically important information as part of a computation. You of course have the option of dropping labels with missing data via the **dropna** function.

Name attribute

Series can also have a `name` attribute:

```
In [32]: s = pd.Series(np.random.randn(5), name="something")

In [33]: s
Out[33]:
0   -0.494929
1    1.071804
2    0.721555
3   -0.706771
4   -1.039575
Name: something, dtype: float64
```

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```
In [34]: s.name
Out[34]: 'something'
```

The Series `name` will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.

You can rename a Series with the *pandas.Series.rename()* method.

```
In [35]: s2 = s.rename("different")

In [36]: s2.name
Out[36]: 'different'
```

Note that `s` and `s2` refer to different objects.

2.2.2 DataFrame

DataFrame is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- Structured or record ndarray
- A `Series`
- Another `DataFrame`

Along with the data, you can optionally pass **index** (row labels) and **columns** (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.

Note: When the data is a dict, and `columns` is not specified, the `DataFrame` columns will be ordered by the dict's insertion order, if you are using Python version >= 3.6 and pandas >= 0.23.

If you are using Python < 3.6 or pandas < 0.23, and `columns` is not specified, the `DataFrame` columns will be the lexically ordered list of dict keys.

From dict of Series or dicts

The resulting **index** will be the **union** of the indexes of the various Series. If there are any nested dicts, these will first be converted to Series. If no columns are passed, the columns will be the ordered list of dict keys.

```
In [37]: d = {
   ....:     "one": pd.Series([1.0, 2.0, 3.0], index=["a", "b", "c"]),
   ....:     "two": pd.Series([1.0, 2.0, 3.0, 4.0], index=["a", "b", "c", "d"]),
   ....: }
   ....:

In [38]: df = pd.DataFrame(d)
```

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```
In [39]: df
Out[39]:
   one  two
a  1.0  1.0
b  2.0  2.0
c  3.0  3.0
d  NaN  4.0

In [40]: pd.DataFrame(d, index=["d", "b", "a"])
Out[40]:
   one  two
d  NaN  4.0
b  2.0  2.0
a  1.0  1.0

In [41]: pd.DataFrame(d, index=["d", "b", "a"], columns=["two", "three"])
Out[41]:
   two three
d  4.0   NaN
b  2.0   NaN
a  1.0   NaN
```

The row and column labels can be accessed respectively by accessing the **index** and **columns** attributes:

Note: When a particular set of columns is passed along with a dict of data, the passed columns override the keys in the dict.

```
In [42]: df.index
Out[42]: Index(['a', 'b', 'c', 'd'], dtype='object')

In [43]: df.columns
Out[43]: Index(['one', 'two'], dtype='object')
```

From dict of ndarrays / lists

The ndarrays must all be the same length. If an index is passed, it must clearly also be the same length as the arrays. If no index is passed, the result will be `range(n)`, where `n` is the array length.

```
In [44]: d = {"one": [1.0, 2.0, 3.0, 4.0], "two": [4.0, 3.0, 2.0, 1.0]}

In [45]: pd.DataFrame(d)
Out[45]:
   one  two
0  1.0  4.0
1  2.0  3.0
2  3.0  2.0
3  4.0  1.0

In [46]: pd.DataFrame(d, index=["a", "b", "c", "d"])
Out[46]:
   one  two
a  1.0  4.0
```

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```
b  2.0  3.0
c  3.0  2.0
d  4.0  1.0
```

From structured or record array

This case is handled identically to a dict of arrays.

```
In [47]: data = np.zeros((2,), dtype=[("A", "i4"), ("B", "f4"), ("C", "a10")])

In [48]: data[:] = [(1, 2.0, "Hello"), (2, 3.0, "World")]

In [49]: pd.DataFrame(data)
Out[49]:
   A    B         C
0  1  2.0  b'Hello'
1  2  3.0  b'World'

In [50]: pd.DataFrame(data, index=["first", "second"])
Out[50]:
        A    B         C
first   1  2.0  b'Hello'
second  2  3.0  b'World'

In [51]: pd.DataFrame(data, columns=["C", "A", "B"])
Out[51]:
          C  A    B
0  b'Hello'  1  2.0
1  b'World'  2  3.0
```

Note: DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.

From a list of dicts

```
In [52]: data2 = [{"a": 1, "b": 2}, {"a": 5, "b": 10, "c": 20}]

In [53]: pd.DataFrame(data2)
Out[53]:
   a   b     c
0  1   2   NaN
1  5  10  20.0

In [54]: pd.DataFrame(data2, index=["first", "second"])
Out[54]:
        a   b     c
first   1   2   NaN
second  5  10  20.0

In [55]: pd.DataFrame(data2, columns=["a", "b"])
Out[55]:
   a   b
```

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```
0  1   2
1  5  10
```

From a dict of tuples

You can automatically create a MultiIndexed frame by passing a tuples dictionary.

```
In [56]: pd.DataFrame(
   ....:     {
   ....:         ("a", "b"): {("A", "B"): 1, ("A", "C"): 2},
   ....:         ("a", "a"): {("A", "C"): 3, ("A", "B"): 4},
   ....:         ("a", "c"): {("A", "B"): 5, ("A", "C"): 6},
   ....:         ("b", "a"): {("A", "C"): 7, ("A", "B"): 8},
   ....:         ("b", "b"): {("A", "D"): 9, ("A", "B"): 10},
   ....:     }
   ....: )
   ....:
Out[56]:
       a              b
       b    a    c    a     b
A B  1.0  4.0  5.0  8.0  10.0
  C  2.0  3.0  6.0  7.0   NaN
  D  NaN  NaN  NaN  NaN   9.0
```

From a Series

The result will be a DataFrame with the same index as the input Series, and with one column whose name is the original name of the Series (only if no other column name provided).

From a list of namedtuples

The field names of the first `namedtuple` in the list determine the columns of the `DataFrame`. The remaining namedtuples (or tuples) are simply unpacked and their values are fed into the rows of the `DataFrame`. If any of those tuples is shorter than the first `namedtuple` then the later columns in the corresponding row are marked as missing values. If any are longer than the first `namedtuple`, a `ValueError` is raised.

```
In [57]: from collections import namedtuple

In [58]: Point = namedtuple("Point", "x y")

In [59]: pd.DataFrame([Point(0, 0), Point(0, 3), (2, 3)])
Out[59]:
   x  y
0  0  0
1  0  3
2  2  3

In [60]: Point3D = namedtuple("Point3D", "x y z")

In [61]: pd.DataFrame([Point3D(0, 0, 0), Point3D(0, 3, 5), Point(2, 3)])
Out[61]:
   x  y    z
```

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```
0  0  0  0.0
1  0  3  5.0
2  2  3  NaN
```

From a list of dataclasses

New in version 1.1.0.

Data Classes as introduced in PEP557, can be passed into the DataFrame constructor. Passing a list of dataclasses is equivalent to passing a list of dictionaries.

Please be aware, that all values in the list should be dataclasses, mixing types in the list would result in a TypeError.

```
In [62]: from dataclasses import make_dataclass

In [63]: Point = make_dataclass("Point", [("x", int), ("y", int)])

In [64]: pd.DataFrame([Point(0, 0), Point(0, 3), Point(2, 3)])
Out[64]:
   x  y
0  0  0
1  0  3
2  2  3
```

Missing data

Much more will be said on this topic in the *Missing data* section. To construct a DataFrame with missing data, we use `np.nan` to represent missing values. Alternatively, you may pass a `numpy.MaskedArray` as the data argument to the DataFrame constructor, and its masked entries will be considered missing.

Alternate constructors

DataFrame.from_dict

`DataFrame.from_dict` takes a dict of dicts or a dict of array-like sequences and returns a DataFrame. It operates like the `DataFrame` constructor except for the `orient` parameter which is `'columns'` by default, but which can be set to `'index'` in order to use the dict keys as row labels.

```
In [65]: pd.DataFrame.from_dict(dict([("A", [1, 2, 3]), ("B", [4, 5, 6])]))
Out[65]:
   A  B
0  1  4
1  2  5
2  3  6
```

If you pass `orient='index'`, the keys will be the row labels. In this case, you can also pass the desired column names:

```
In [66]: pd.DataFrame.from_dict(
   ....:     dict([("A", [1, 2, 3]), ("B", [4, 5, 6])]),
   ....:     orient="index",
   ....:     columns=["one", "two", "three"],
   ....: )
   ....:
Out[66]:
```

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```
   one  two  three
A    1    2      3
B    4    5      6
```

DataFrame.from_records

`DataFrame.from_records` takes a list of tuples or an ndarray with structured dtype. It works analogously to the normal `DataFrame` constructor, except that the resulting DataFrame index may be a specific field of the structured dtype. For example:

```
In [67]: data
Out[67]:
array([(1, 2., b'Hello'), (2, 3., b'World')],
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])

In [68]: pd.DataFrame.from_records(data, index="C")
Out[68]:
          A    B
C
b'Hello'  1  2.0
b'World'  2  3.0
```

Column selection, addition, deletion

You can treat a DataFrame semantically like a dict of like-indexed Series objects. Getting, setting, and deleting columns works with the same syntax as the analogous dict operations:

```
In [69]: df["one"]
Out[69]:
a    1.0
b    2.0
c    3.0
d    NaN
Name: one, dtype: float64

In [70]: df["three"] = df["one"] * df["two"]

In [71]: df["flag"] = df["one"] > 2

In [72]: df
Out[72]:
   one  two  three   flag
a  1.0  1.0    1.0  False
b  2.0  2.0    4.0  False
c  3.0  3.0    9.0   True
d  NaN  4.0    NaN  False
```

Columns can be deleted or popped like with a dict:

```
In [73]: del df["two"]

In [74]: three = df.pop("three")

In [75]: df
Out[75]:
```

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```
   one   flag
a  1.0  False
b  2.0  False
c  3.0   True
d  NaN  False
```

When inserting a scalar value, it will naturally be propagated to fill the column:

```
In [76]: df["foo"] = "bar"

In [77]: df
Out[77]:
   one   flag  foo
a  1.0  False  bar
b  2.0  False  bar
c  3.0   True  bar
d  NaN  False  bar
```

When inserting a Series that does not have the same index as the DataFrame, it will be conformed to the DataFrame's index:

```
In [78]: df["one_trunc"] = df["one"][:2]

In [79]: df
Out[79]:
   one   flag  foo  one_trunc
a  1.0  False  bar        1.0
b  2.0  False  bar        2.0
c  3.0   True  bar        NaN
d  NaN  False  bar        NaN
```

You can insert raw ndarrays but their length must match the length of the DataFrame's index.

By default, columns get inserted at the end. The `insert` function is available to insert at a particular location in the columns:

```
In [80]: df.insert(1, "bar", df["one"])

In [81]: df
Out[81]:
   one  bar   flag  foo  one_trunc
a  1.0  1.0  False  bar        1.0
b  2.0  2.0  False  bar        2.0
c  3.0  3.0   True  bar        NaN
d  NaN  NaN  False  bar        NaN
```

Assigning new columns in method chains

Inspired by dplyr's `mutate` verb, DataFrame has an *`assign()`* method that allows you to easily create new columns that are potentially derived from existing columns.

```
In [82]: iris = pd.read_csv("data/iris.data")

In [83]: iris.head()
Out[83]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name
0          5.1         3.5          1.4         0.2  Iris-setosa
1          4.9         3.0          1.4         0.2  Iris-setosa
2          4.7         3.2          1.3         0.2  Iris-setosa
3          4.6         3.1          1.5         0.2  Iris-setosa
4          5.0         3.6          1.4         0.2  Iris-setosa

In [84]: iris.assign(sepal_ratio=iris["SepalWidth"] / iris["SepalLength"]).head()
Out[84]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa     0.686275
1          4.9         3.0          1.4         0.2  Iris-setosa     0.612245
2          4.7         3.2          1.3         0.2  Iris-setosa     0.680851
3          4.6         3.1          1.5         0.2  Iris-setosa     0.673913
4          5.0         3.6          1.4         0.2  Iris-setosa     0.720000
```

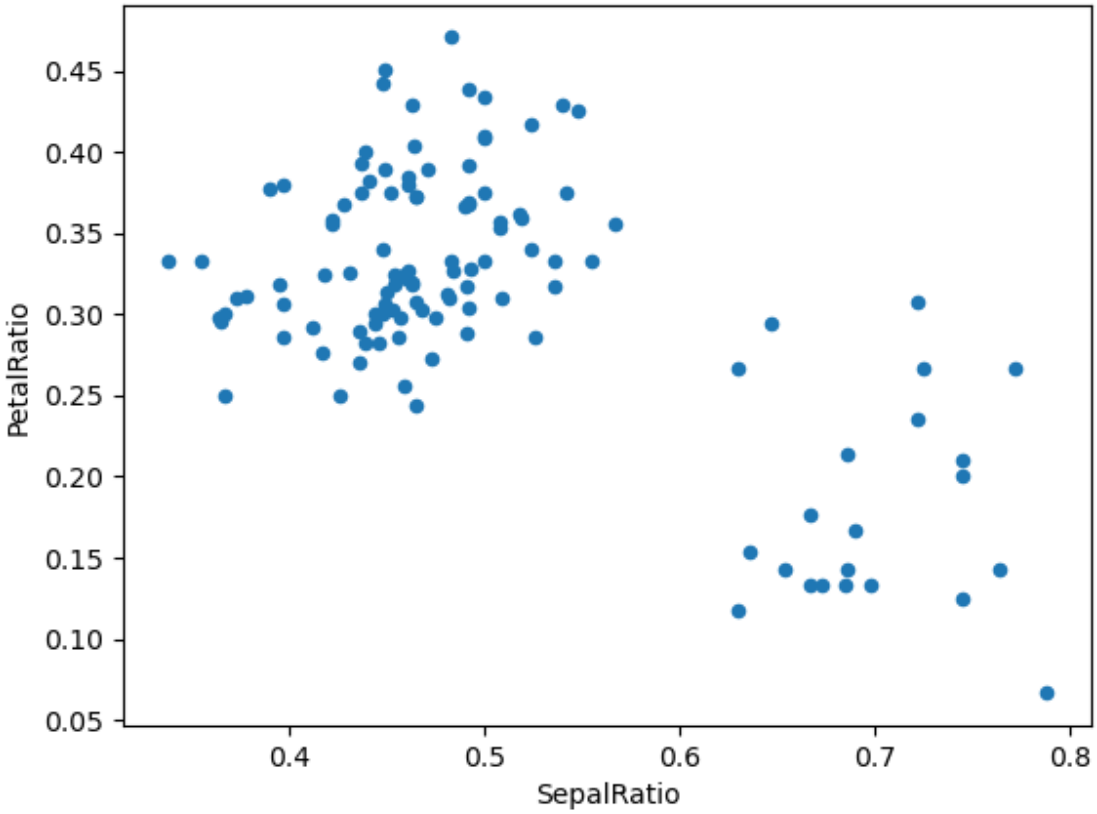
In the example above, we inserted a precomputed value. We can also pass in a function of one argument to be evaluated on the DataFrame being assigned to.

```
In [85]: iris.assign(sepal_ratio=lambda x: (x["SepalWidth"] / x["SepalLength"])).
↪head()
Out[85]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa     0.686275
1          4.9         3.0          1.4         0.2  Iris-setosa     0.612245
2          4.7         3.2          1.3         0.2  Iris-setosa     0.680851
3          4.6         3.1          1.5         0.2  Iris-setosa     0.673913
4          5.0         3.6          1.4         0.2  Iris-setosa     0.720000
```

`assign` **always** returns a copy of the data, leaving the original DataFrame untouched.

Passing a callable, as opposed to an actual value to be inserted, is useful when you don't have a reference to the DataFrame at hand. This is common when using `assign` in a chain of operations. For example, we can limit the DataFrame to just those observations with a Sepal Length greater than 5, calculate the ratio, and plot:

```
In [86]: (
   ....:     iris.query("SepalLength > 5")
   ....:     .assign(
   ....:         SepalRatio=lambda x: x.SepalWidth / x.SepalLength,
   ....:         PetalRatio=lambda x: x.PetalWidth / x.PetalLength,
   ....:     )
   ....:     .plot(kind="scatter", x="SepalRatio", y="PetalRatio")
   ....: )
   ....:
Out[86]: <AxesSubplot:xlabel='SepalRatio', ylabel='PetalRatio'>
```



Since a function is passed in, the function is computed on the DataFrame being assigned to. Importantly, this is the DataFrame that's been filtered to those rows with sepal length greater than 5. The filtering happens first, and then the ratio calculations. This is an example where we didn't have a reference to the *filtered* DataFrame available.

The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. A *copy* of the original DataFrame is returned, with the new values inserted.

Starting with Python 3.6 the order of `**kwargs` is preserved. This allows for *dependent* assignment, where an expression later in `**kwargs` can refer to a column created earlier in the same *`assign()`*.

```
In [87]: dfa = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})

In [88]: dfa.assign(C=lambda x: x["A"] + x["B"], D=lambda x: x["A"] + x["C"])
Out[88]:
   A  B  C   D
0  1  4  5   6
1  2  5  7   9
2  3  6  9  12
```

In the second expression, `x['C']` will refer to the newly created column, that's equal to `dfa['A'] + dfa['B']`.

Indexing / selection

The basics of indexing are as follows:

Operation	Syntax	Result
Select column	`df[col]`	Series
Select row by label	`df.loc[label]`	Series
Select row by integer location	`df.iloc[loc]`	Series
Slice rows	`df[5:10]`	DataFrame
Select rows by boolean vector	`df[bool_vec]`	DataFrame

Row selection, for example, returns a Series whose index is the columns of the DataFrame:

```
In [89]: df.loc["b"]
Out[89]:
one             2.0
bar             2.0
flag          False
foo             bar
one_trunc       2.0
Name: b, dtype: object

In [90]: df.iloc[2]
Out[90]:
one             3.0
bar             3.0
flag           True
foo             bar
one_trunc       NaN
Name: c, dtype: object
```

For a more exhaustive treatment of sophisticated label-based indexing and slicing, see the *section on indexing*. We will address the fundamentals of reindexing / conforming to new sets of labels in the *section on reindexing*.

Data alignment and arithmetic

Data alignment between DataFrame objects automatically align on **both the columns and the index (row labels)**. Again, the resulting object will have the union of the column and row labels.

```
In [91]: df = pd.DataFrame(np.random.randn(10, 4), columns=["A", "B", "C", "D"])

In [92]: df2 = pd.DataFrame(np.random.randn(7, 3), columns=["A", "B", "C"])

In [93]: df + df2
Out[93]:
          A         B         C   D
0  0.045691 -0.014138  1.380871 NaN
1 -0.955398 -1.501007  0.037181 NaN
2 -0.662690  1.534833 -0.859691 NaN
3 -2.452949  1.237274 -0.133712 NaN
4  1.414490  1.951676 -2.320422 NaN
5 -0.494922 -1.649727 -1.084601 NaN
6 -1.047551 -0.748572 -0.805479 NaN
7       NaN       NaN       NaN NaN
```

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```
8       NaN       NaN       NaN NaN
9       NaN       NaN       NaN NaN
```

When doing an operation between DataFrame and Series, the default behavior is to align the Series **index** on the DataFrame **columns**, thus broadcasting row-wise. For example:

```
In [94]: df - df.iloc[0]
Out[94]:
          A         B         C         D
0  0.000000  0.000000  0.000000  0.000000
1 -1.359261 -0.248717 -0.453372 -1.754659
2  0.253128  0.829678  0.010026 -1.991234
3 -1.311128  0.054325 -1.724913 -1.620544
4  0.573025  1.500742 -0.676070  1.367331
5 -1.741248  0.781993 -1.241620 -2.053136
6 -1.240774 -0.869551 -0.153282  0.000430
7 -0.743894  0.411013 -0.929563 -0.282386
8 -1.194921  1.320690  0.238224 -1.482644
9  2.293786  1.856228  0.773289 -1.446531
```

For explicit control over the matching and broadcasting behavior, see the section on *flexible binary operations*.

Operations with scalars are just as you would expect:

```
In [95]: df * 5 + 2
Out[95]:
           A         B         C          D
0   3.359299 -0.124862  4.835102   3.381160
1  -3.437003 -1.368449  2.568242  -5.392133
2   4.624938  4.023526  4.885230  -6.575010
3  -3.196342  0.146766 -3.789461  -4.721559
4   6.224426  7.378849  1.454750  10.217815
5  -5.346940  3.785103 -1.373001  -6.884519
6  -2.844569 -4.472618  4.068691   3.383309
7  -0.360173  1.930201  0.187285   1.969232
8  -2.615303  6.478587  6.026220  -4.032059
9  14.828230  9.156280  8.701544  -3.851494

In [96]: 1 / df
Out[96]:
          A          B         C           D
0  3.678365  -2.353094  1.763605    3.620145
1 -0.919624  -1.484363  8.799067   -0.676395
2  1.904807   2.470934  1.732964   -0.583090
3 -0.962215  -2.697986 -0.863638   -0.743875
4  1.183593   0.929567 -9.170108    0.608434
5 -0.680555   2.800959 -1.482360   -0.562777
6 -1.032084  -0.772485  2.416988    3.614523
7 -2.118489 -71.634509 -2.758294 -162.507295
8 -1.083352   1.116424  1.241860   -0.828904
9  0.389765   0.698687  0.746097   -0.854483

In [97]: df ** 4
Out[97]:
           A             B         C             D
0   0.005462  3.261689e-02  0.103370  5.822320e-03
1   1.398165  2.059869e-01  0.000167  4.777482e+00
```

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```
2   0.075962  2.682596e-02  0.110877  8.650845e+00
3   1.166571  1.887302e-02  1.797515  3.265879e+00
4   0.509555  1.339298e+00  0.000141  7.297019e+00
5   4.661717  1.624699e-02  0.207103  9.969092e+00
6   0.881334  2.808277e+00  0.029302  5.858632e-03
7   0.049647  3.797614e-08  0.017276  1.433866e-09
8   0.725974  6.437005e-01  0.420446  2.118275e+00
9  43.329821  4.196326e+00  3.227153  1.875802e+00
```

Boolean operators work as well:

```
In [98]: df1 = pd.DataFrame({"a": [1, 0, 1], "b": [0, 1, 1]}, dtype=bool)

In [99]: df2 = pd.DataFrame({"a": [0, 1, 1], "b": [1, 1, 0]}, dtype=bool)

In [100]: df1 & df2
Out[100]:
       a      b
0  False  False
1  False   True
2   True  False

In [101]: df1 | df2
Out[101]:
      a     b
0  True  True
1  True  True
2  True  True

In [102]: df1 ^ df2
Out[102]:
       a      b
0   True   True
1   True  False
2  False   True

In [103]: -df1
Out[103]:
       a      b
0  False   True
1   True  False
2  False  False
```

Transposing

To transpose, access the `T` attribute (also the `transpose` function), similar to an ndarray:

```
# only show the first 5 rows
In [104]: df[:5].T
Out[104]:
          0         1         2         3         4
A  0.271860 -1.087401  0.524988 -1.039268  0.844885
B -0.424972 -0.673690  0.404705 -0.370647  1.075770
C  0.567020  0.113648  0.577046 -1.157892 -0.109050
D  0.276232 -1.478427 -1.715002 -1.344312  1.643563
```

DataFrame interoperability with NumPy functions

Elementwise NumPy ufuncs (log, exp, sqrt, ...) and various other NumPy functions can be used with no issues on Series and DataFrame, assuming the data within are numeric:

```
In [105]: np.exp(df)
Out[105]:
          A         B         C         D
0  1.312403  0.653788  1.763006  1.318154
1  0.337092  0.509824  1.120358  0.227996
2  1.690438  1.498861  1.780770  0.179963
3  0.353713  0.690288  0.314148  0.260719
4  2.327710  2.932249  0.896686  5.173571
5  0.230066  1.429065  0.509360  0.169161
6  0.379495  0.274028  1.512461  1.318720
7  0.623732  0.986137  0.695904  0.993865
8  0.397301  2.449092  2.237242  0.299269
9 13.009059  4.183951  3.820223  0.310274

In [106]: np.asarray(df)
Out[106]:
array([[ 0.2719, -0.425 ,  0.567 ,  0.2762],
       [-1.0874, -0.6737,  0.1136, -1.4784],
       [ 0.525 ,  0.4047,  0.577 , -1.715 ],
       [-1.0393, -0.3706, -1.1579, -1.3443],
       [ 0.8449,  1.0758, -0.109 ,  1.6436],
       [-1.4694,  0.357 , -0.6746, -1.7769],
       [-0.9689, -1.2945,  0.4137,  0.2767],
       [-0.472 , -0.014 , -0.3625, -0.0062],
       [-0.9231,  0.8957,  0.8052, -1.2064],
       [ 2.5656,  1.4313,  1.3403, -1.1703]])
```

DataFrame is not intended to be a drop-in replacement for ndarray as its indexing semantics and data model are quite different in places from an n-dimensional array.

Series implements `__array_ufunc__`, which allows it to work with NumPy's universal functions.

The ufunc is applied to the underlying array in a Series.

```
In [107]: ser = pd.Series([1, 2, 3, 4])

In [108]: np.exp(ser)
Out[108]:
0     2.718282
1     7.389056
2    20.085537
3    54.598150
dtype: float64
```

Changed in version 0.25.0: When multiple `Series` are passed to a ufunc, they are aligned before performing the operation.

Like other parts of the library, pandas will automatically align labeled inputs as part of a ufunc with multiple inputs. For example, using `numpy.remainder()` on two *Series* with differently ordered labels will align before the operation.

```
In [109]: ser1 = pd.Series([1, 2, 3], index=["a", "b", "c"])
```

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```
In [110]: ser2 = pd.Series([1, 3, 5], index=["b", "a", "c"])

In [111]: ser1
Out[111]:
a    1
b    2
c    3
dtype: int64

In [112]: ser2
Out[112]:
b    1
a    3
c    5
dtype: int64

In [113]: np.remainder(ser1, ser2)
Out[113]:
a    1
b    0
c    3
dtype: int64
```

As usual, the union of the two indices is taken, and non-overlapping values are filled with missing values.

```
In [114]: ser3 = pd.Series([2, 4, 6], index=["b", "c", "d"])

In [115]: ser3
Out[115]:
b    2
c    4
d    6
dtype: int64

In [116]: np.remainder(ser1, ser3)
Out[116]:
a    NaN
b    0.0
c    3.0
d    NaN
dtype: float64
```

When a binary ufunc is applied to a *Series* and *Index*, the Series implementation takes precedence and a Series is returned.

```
In [117]: ser = pd.Series([1, 2, 3])

In [118]: idx = pd.Index([4, 5, 6])

In [119]: np.maximum(ser, idx)
Out[119]:
0    4
1    5
2    6
dtype: int64
```

NumPy ufuncs are safe to apply to *Series* backed by non-ndarray arrays, for example *arrays.SparseArray*

(see *Sparse calculation*). If possible, the ufunc is applied without converting the underlying data to an ndarray.

Console display

Very large DataFrames will be truncated to display them in the console. You can also get a summary using `info()`. (Here I am reading a CSV version of the **baseball** dataset from the **plyr** R package):

```
In [120]: baseball = pd.read_csv("data/baseball.csv")

In [121]: print(baseball)
       id     player  year  stint team  lg   g   ab   r    h  X2b  X3b  hr   rbi   sb␣
↪  cs  bb    so  ibb  hbp   sh   sf  gidp
0   88641  womacto01  2006      2  CHN  NL  19   50   6   14    1    0   1   2.0  1.0␣
↪ 1.0   4   4.0  0.0  0.0  3.0  0.0   0.0
1   88643  schilcu01  2006      1  BOS  AL  31    2   0    1    0    0   0   0.0  0.0␣
↪ 0.0   0   1.0  0.0  0.0  0.0  0.0   0.0
..    ...        ...   ...    ...  ...  ..  ..  ...  ..  ...  ...  ...  ..   ...  ...␣
↪ ...  ..   ...  ...  ...  ...  ...   ...
98  89533   aloumo01  2007      1  NYN  NL  87  328  51  112   19    1  13  49.0  3.0␣
↪ 0.0  27  30.0  5.0  2.0  0.0  3.0  13.0
99  89534  alomasa02  2007      1  NYN  NL   8   22   1    3    1    0   0   0.0  0.0␣
↪ 0.0   0   3.0  0.0  0.0  0.0  0.0   0.0

[100 rows x 23 columns]

In [122]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 23 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   id      100 non-null    int64
 1   player  100 non-null    object
 2   year    100 non-null    int64
 3   stint   100 non-null    int64
 4   team    100 non-null    object
 5   lg      100 non-null    object
 6   g       100 non-null    int64
 7   ab      100 non-null    int64
 8   r       100 non-null    int64
 9   h       100 non-null    int64
 10  X2b     100 non-null    int64
 11  X3b     100 non-null    int64
 12  hr      100 non-null    int64
 13  rbi     100 non-null    float64
 14  sb      100 non-null    float64
 15  cs      100 non-null    float64
 16  bb      100 non-null    int64
 17  so      100 non-null    float64
 18  ibb     100 non-null    float64
 19  hbp     100 non-null    float64
 20  sh      100 non-null    float64
 21  sf      100 non-null    float64
 22  gidp    100 non-null    float64
dtypes: float64(9), int64(11), object(3)
memory usage: 18.1+ KB
```

However, using `to_string` will return a string representation of the DataFrame in tabular form, though it won't

always fit the console width:

```
In [123]: print(baseball.iloc[-20:, :12].to_string())
       id     player  year  stint team  lg    g   ab   r    h  X2b  X3b
80  89474  finlest01  2007      1  COL  NL   43   94   9   17    3    0
81  89480  embreal01  2007      1  OAK  AL    4    0   0    0    0    0
82  89481  edmonji01  2007      1  SLN  NL  117  365  39   92   15    2
83  89482  easleda01  2007      1  NYN  NL   76  193  24   54    6    0
84  89489  delgaca01  2007      1  NYN  NL  139  538  71  139   30    0
85  89493  cormirh01  2007      1  CIN  NL    6    0   0    0    0    0
86  89494  coninje01  2007      2  NYN  NL   21   41   2    8    2    0
87  89495  coninje01  2007      1  CIN  NL   80  215  23   57   11    1
88  89497  clemero02  2007      1  NYA  AL    2    2   0    1    0    0
89  89498  claytro01  2007      2  BOS  AL    8    6   1    0    0    0
90  89499  claytro01  2007      1  TOR  AL   69  189  23   48   14    0
91  89501  cirilje01  2007      2  ARI  NL   28   40   6    8    4    0
92  89502  cirilje01  2007      1  MIN  AL   50  153  18   40    9    2
93  89521  bondsba01  2007      1  SFN  NL  126  340  75   94   14    0
94  89523  biggicr01  2007      1  HOU  NL  141  517  68  130   31    3
95  89525  benitar01  2007      2  FLO  NL   34    0   0    0    0    0
96  89526  benitar01  2007      1  SFN  NL   19    0   0    0    0    0
97  89530  ausmubr01  2007      1  HOU  NL  117  349  38   82   16    3
98  89533   aloumo01  2007      1  NYN  NL   87  328  51  112   19    1
99  89534  alomasa02  2007      1  NYN  NL    8   22   1    3    1    0
```

Wide DataFrames will be printed across multiple rows by default:

```
In [124]: pd.DataFrame(np.random.randn(3, 12))
Out[124]:
          0         1         2         3         4         5         6         7
↪    8         9         10        11
0 -1.226825  0.769804 -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734  0.
↪959726 -1.110336 -0.619976  0.149748
1 -0.732339  0.687738  0.176444  0.403310 -0.154951  0.301624 -2.179861 -1.369849 -0.
↪954208  1.462696 -1.743161 -0.826591
2 -0.345352  1.314232  0.690579  0.995761  2.396780  0.014871  3.357427 -0.317441 -1.
↪236269  0.896171 -0.487602 -0.082240
```

You can change how much to print on a single row by setting the `display.width` option:

```
In [125]: pd.set_option("display.width", 40)  # default is 80

In [126]: pd.DataFrame(np.random.randn(3, 12))
Out[126]:
          0         1         2         3         4         5         6         7
↪    8         9         10        11
0 -2.182937  0.380396  0.084844  0.432390  1.519970 -0.493662  0.600178  0.274230  0.
↪132885 -0.023688  2.410179  1.450520
1  0.206053 -0.251905 -2.213588  1.063327  1.266143  0.299368 -0.863838  0.408204 -1.
↪048089 -0.025747 -0.988387  0.094055
2  1.262731  1.289997  0.082423 -0.055758  0.536580 -0.489682  0.369374 -0.034571 -2.
↪484478 -0.281461  0.030711  0.109121
```

You can adjust the max width of the individual columns by setting `display.max_colwidth`

```
In [127]: datafile = {
   .....:     "filename": ["filename_01", "filename_02"],
   .....:     "path": [
```

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```
   .....:         "media/user_name/storage/folder_01/filename_01",
   .....:         "media/user_name/storage/folder_02/filename_02",
   .....:     ],
   .....: }
   .....:

In [128]: pd.set_option("display.max_colwidth", 30)

In [129]: pd.DataFrame(datafile)
Out[129]:
      filename                          path
0  filename_01  media/user_name/storage/fo...
1  filename_02  media/user_name/storage/fo...

In [130]: pd.set_option("display.max_colwidth", 100)

In [131]: pd.DataFrame(datafile)
Out[131]:
      filename                                              path
0  filename_01  media/user_name/storage/folder_01/filename_01
1  filename_02  media/user_name/storage/folder_02/filename_02
```

You can also disable this feature via the `expand_frame_repr` option. This will print the table in one block.

DataFrame column attribute access and IPython completion

If a DataFrame column label is a valid Python variable name, the column can be accessed like an attribute:

```
In [132]: df = pd.DataFrame({"foo1": np.random.randn(5), "foo2": np.random.randn(5)})

In [133]: df
Out[133]:
       foo1      foo2
0  1.126203  0.781836
1 -0.977349 -1.071357
2  1.474071  0.441153
3 -0.064034  2.353925
4 -1.282782  0.583787

In [134]: df.foo1
Out[134]:
0    1.126203
1   -0.977349
2    1.474071
3   -0.064034
4   -1.282782
Name: foo1, dtype: float64
```

The columns are also connected to the IPython completion mechanism so they can be tab-completed:

```
In [5]: df.fo<TAB>  # noqa: E225, E999
df.foo1  df.foo2
```

2.3 Essential basic functionality

Here we discuss a lot of the essential functionality common to the pandas data structures. To begin, let's create some example objects like we did in the *10 minutes to pandas* section:

```
In [1]: index = pd.date_range("1/1/2000", periods=8)

In [2]: s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])

In [3]: df = pd.DataFrame(np.random.randn(8, 3), index=index, columns=["A", "B", "C"])
```

2.3.1 Head and tail

To view a small sample of a Series or DataFrame object, use the `head()` and `tail()` methods. The default number of elements to display is five, but you may pass a custom number.

```
In [4]: long_series = pd.Series(np.random.randn(1000))

In [5]: long_series.head()
Out[5]:
0   -1.157892
1   -1.344312
2    0.844885
3    1.075770
4   -0.109050
dtype: float64

In [6]: long_series.tail(3)
Out[6]:
997   -0.289388
998   -1.020544
999    0.589993
dtype: float64
```

2.3.2 Attributes and underlying data

pandas objects have a number of attributes enabling you to access the metadata

- **shape**: gives the axis dimensions of the object, consistent with ndarray
- **Axis labels**
  - **Series**: *index* (only axis)
  - **DataFrame**: *index* (rows) and *columns*

Note, **these attributes can be safely assigned to**!

```
In [7]: df[:2]
Out[7]:
                   A         B         C
2000-01-01 -0.173215  0.119209 -1.044236
2000-01-02 -0.861849 -2.104569 -0.494929

In [8]: df.columns = [x.lower() for x in df.columns]
```

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```
In [9]: df
Out[9]:
                   a         b         c
2000-01-01 -0.173215  0.119209 -1.044236
2000-01-02 -0.861849 -2.104569 -0.494929
2000-01-03  1.071804  0.721555 -0.706771
2000-01-04 -1.039575  0.271860 -0.424972
2000-01-05  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427
2000-01-07  0.524988  0.404705  0.577046
2000-01-08 -1.715002 -1.039268 -0.370647
```

pandas objects (*Index*, *Series*, *DataFrame*) can be thought of as containers for arrays, which hold the actual data and do the actual computation. For many types, the underlying array is a `numpy.ndarray`. However, pandas and 3rd party libraries may *extend* NumPy's type system to add support for custom arrays (see *dtypes*).

To get the actual data inside a *Index* or *Series*, use the `.array` property

```
In [10]: s.array
Out[10]:
<PandasArray>
[ 0.4691122999071863, -0.2828633443286633, -1.5090585031735124,
 -1.1356323710171934,  1.2121120250208506]
Length: 5, dtype: float64

In [11]: s.index.array
Out[11]:
<PandasArray>
['a', 'b', 'c', 'd', 'e']
Length: 5, dtype: object
```

array will always be an *ExtensionArray*. The exact details of what an *ExtensionArray* is and why pandas uses them are a bit beyond the scope of this introduction. See *dtypes* for more.

If you know you need a NumPy array, use *to_numpy()* or `numpy.asarray()`.

```
In [12]: s.to_numpy()
Out[12]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])

In [13]: np.asarray(s)
Out[13]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])
```

When the Series or Index is backed by an *ExtensionArray*, *to_numpy()* may involve copying data and coercing values. See *dtypes* for more.

to_numpy() gives some control over the `dtype` of the resulting `numpy.ndarray`. For example, consider datetimes with timezones. NumPy doesn't have a dtype to represent timezone-aware datetimes, so there are two possibly useful representations:

1. An object-dtype `numpy.ndarray` with *Timestamp* objects, each with the correct `tz`
2. A `datetime64[ns]` -dtype `numpy.ndarray`, where the values have been converted to UTC and the timezone discarded

Timezones may be preserved with `dtype=object`

```
In [14]: ser = pd.Series(pd.date_range("2000", periods=2, tz="CET"))

In [15]: ser.to_numpy(dtype=object)
Out[15]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or thrown away with `dtype='datetime64[ns]'`

```
In [16]: ser.to_numpy(dtype="datetime64[ns]")
Out[16]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

Getting the "raw data" inside a *DataFrame* is possibly a bit more complex. When your `DataFrame` only has a single data type for all the columns, *DataFrame.to_numpy()* will return the underlying data:

```
In [17]: df.to_numpy()
Out[17]:
array([[-0.1732,  0.1192, -1.0442],
       [-0.8618, -2.1046, -0.4949],
       [ 1.0718,  0.7216, -0.7068],
       [-1.0396,  0.2719, -0.425 ],
       [ 0.567 ,  0.2762, -1.0874],
       [-0.6737,  0.1136, -1.4784],
       [ 0.525 ,  0.4047,  0.577 ],
       [-1.715 , -1.0393, -0.3706]])
```

If a DataFrame contains homogeneously-typed data, the ndarray can actually be modified in-place, and the changes will be reflected in the data structure. For heterogeneous data (e.g. some of the DataFrame's columns are not all the same dtype), this will not be the case. The values attribute itself, unlike the axis labels, cannot be assigned to.

Note: When working with heterogeneous data, the dtype of the resulting ndarray will be chosen to accommodate all of the data involved. For example, if strings are involved, the result will be of object dtype. If there are only floats and integers, the resulting array will be of float dtype.

In the past, pandas recommended *Series.values* or *DataFrame.values* for extracting the data from a Series or DataFrame. You'll still find references to these in old code bases and online. Going forward, we recommend avoiding `.values` and using `.array` or `.to_numpy()`. `.values` has the following drawbacks:

1. When your Series contains an *extension type*, it's unclear whether *Series.values* returns a NumPy array or the extension array. *Series.array* will always return an *ExtensionArray*, and will never copy data. *Series.to_numpy()* will always return a NumPy array, potentially at the cost of copying / coercing values.
2. When your DataFrame contains a mixture of data types, *DataFrame.values* may involve copying data and coercing values to a common dtype, a relatively expensive operation. *DataFrame.to_numpy()*, being a method, makes it clearer that the returned NumPy array may not be a view on the same data in the DataFrame.

2.3.3 Accelerated operations

pandas has support for accelerating certain types of binary numerical and boolean operations using the `numexpr` library and the `bottleneck` libraries.

These libraries are especially useful when dealing with large data sets, and provide large speedups. `numexpr` uses smart chunking, caching, and multiple cores. `bottleneck` is a set of specialized cython routines that are especially fast when dealing with arrays that have `nans`.

Here is a sample (using 100 column x 100,000 row `DataFrames`):

Operation	0.11.0 (ms)	Prior Version (ms)	Ratio to Prior
`df1 > df2`	13.32	125.35	0.1063
`df1 * df2`	21.71	36.63	0.5928
`df1 + df2`	22.04	36.50	0.6039

You are highly encouraged to install both libraries. See the section *Recommended Dependencies* for more installation info.

These are both enabled to be used by default, you can control this by setting the options:

```
pd.set_option("compute.use_bottleneck", False)
pd.set_option("compute.use_numexpr", False)
```

2.3.4 Flexible binary operations

With binary operations between pandas data structures, there are two key points of interest:

- Broadcasting behavior between higher- (e.g. DataFrame) and lower-dimensional (e.g. Series) objects.
- Missing data in computations.

We will demonstrate how to manage these issues independently, though they can be handled simultaneously.

Matching / broadcasting behavior

DataFrame has the methods *add()*, *sub()*, *mul()*, *div()* and related functions *radd()*, *rsub()*, ... for carrying out binary operations. For broadcasting behavior, Series input is of primary interest. Using these functions, you can use to either match on the *index* or *columns* via the **axis** keyword:

```
In [18]: df = pd.DataFrame(
   ....:     {
   ....:         "one": pd.Series(np.random.randn(3), index=["a", "b", "c"]),
   ....:         "two": pd.Series(np.random.randn(4), index=["a", "b", "c", "d"]),
   ....:         "three": pd.Series(np.random.randn(3), index=["b", "c", "d"]),
   ....:     }
   ....: )
   ....:

In [19]: df
Out[19]:
        one       two     three
a  1.394981  1.772517       NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
```

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```
d       NaN  0.279344 -0.613172

In [20]: row = df.iloc[1]

In [21]: column = df["two"]

In [22]: df.sub(row, axis="columns")
Out[22]:
        one       two     three
a  1.051928 -0.139606       NaN
b  0.000000  0.000000  0.000000
c  0.352192 -0.433754  1.277825
d       NaN -1.632779 -0.562782

In [23]: df.sub(row, axis=1)
Out[23]:
        one       two     three
a  1.051928 -0.139606       NaN
b  0.000000  0.000000  0.000000
c  0.352192 -0.433754  1.277825
d       NaN -1.632779 -0.562782

In [24]: df.sub(column, axis="index")
Out[24]:
        one  two     three
a -0.377535  0.0       NaN
b -1.569069  0.0 -1.962513
c -0.783123  0.0 -0.250933
d       NaN  0.0 -0.892516

In [25]: df.sub(column, axis=0)
Out[25]:
        one  two     three
a -0.377535  0.0       NaN
b -1.569069  0.0 -1.962513
c -0.783123  0.0 -0.250933
d       NaN  0.0 -0.892516
```

Furthermore you can align a level of a MultiIndexed DataFrame with a Series.

```
In [26]: dfmi = df.copy()

In [27]: dfmi.index = pd.MultiIndex.from_tuples(
   ....:     [(1, "a"), (1, "b"), (1, "c"), (2, "a")], names=["first", "second"]
   ....: )
   ....:

In [28]: dfmi.sub(column, axis=0, level="second")
Out[28]:
                   one       two     three
first second
1     a      -0.377535  0.000000       NaN
      b      -1.569069  0.000000 -1.962513
      c      -0.783123  0.000000 -0.250933
2     a            NaN -1.493173 -2.385688
```

Series and Index also support the `divmod()` builtin. This function takes the floor division and modulo operation at

the same time returning a two-tuple of the same type as the left hand side. For example:

```
In [29]: s = pd.Series(np.arange(10))

In [30]: s
Out[30]:
0    0
1    1
2    2
3    3
4    4
5    5
6    6
7    7
8    8
9    9
dtype: int64

In [31]: div, rem = divmod(s, 3)

In [32]: div
Out[32]:
0    0
1    0
2    0
3    1
4    1
5    1
6    2
7    2
8    2
9    3
dtype: int64

In [33]: rem
Out[33]:
0    0
1    1
2    2
3    0
4    1
5    2
6    0
7    1
8    2
9    0
dtype: int64

In [34]: idx = pd.Index(np.arange(10))

In [35]: idx
Out[35]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype='int64')

In [36]: div, rem = divmod(idx, 3)

In [37]: div
Out[37]: Int64Index([0, 0, 0, 1, 1, 1, 2, 2, 2, 3], dtype='int64')
```

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```
In [38]: rem
Out[38]: Int64Index([0, 1, 2, 0, 1, 2, 0, 1, 2, 0], dtype='int64')
```

We can also do elementwise `divmod()`:

```
In [39]: div, rem = divmod(s, [2, 2, 3, 3, 4, 4, 5, 5, 6, 6])

In [40]: div
Out[40]:
0    0
1    0
2    0
3    1
4    1
5    1
6    1
7    1
8    1
9    1
dtype: int64

In [41]: rem
Out[41]:
0    0
1    1
2    2
3    0
4    0
5    1
6    1
7    2
8    2
9    3
dtype: int64
```

Missing data / operations with fill values

In Series and DataFrame, the arithmetic functions have the option of inputting a *fill_value*, namely a value to substitute when at most one of the values at a location are missing. For example, when adding two DataFrame objects, you may wish to treat NaN as 0 unless both DataFrames are missing that value, in which case the result will be NaN (you can later replace NaN with some other value using `fillna` if you wish).

```
In [42]: df
Out[42]:
        one       two     three
a  1.394981  1.772517       NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d       NaN  0.279344 -0.613172

In [43]: df2
Out[43]:
        one       two     three
a  1.394981  1.772517  1.000000
b  0.343054  1.912123 -0.050390
```

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```
c  0.695246  1.478369  1.227435
d       NaN  0.279344 -0.613172

In [44]: df + df2
Out[44]:
        one       two     three
a  2.789963  3.545034       NaN
b  0.686107  3.824246 -0.100780
c  1.390491  2.956737  2.454870
d       NaN  0.558688 -1.226343

In [45]: df.add(df2, fill_value=0)
Out[45]:
        one       two     three
a  2.789963  3.545034  1.000000
b  0.686107  3.824246 -0.100780
c  1.390491  2.956737  2.454870
d       NaN  0.558688 -1.226343
```

Flexible comparisons

Series and DataFrame have the binary comparison methods `eq`, `ne`, `lt`, `gt`, `le`, and `ge` whose behavior is analogous to the binary arithmetic operations described above:

```
In [46]: df.gt(df2)
Out[46]:
     one    two  three
a  False  False  False
b  False  False  False
c  False  False  False
d  False  False  False

In [47]: df2.ne(df)
Out[47]:
     one    two  three
a  False  False   True
b  False  False  False
c  False  False  False
d   True  False  False
```

These operations produce a pandas object of the same type as the left-hand-side input that is of dtype `bool`. These `boolean` objects can be used in indexing operations, see the section on *Boolean indexing*.

Boolean reductions

You can apply the reductions: *`empty`*, *`any()`*, *`all()`*, and *`bool()`* to provide a way to summarize a boolean result.

```
In [48]: (df > 0).all()
Out[48]:
one      False
two       True
three    False
dtype: bool
```

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```
In [49]: (df > 0).any()
Out[49]:
one      True
two      True
three    True
dtype: bool
```

You can reduce to a final boolean value.

```
In [50]: (df > 0).any().any()
Out[50]: True
```

You can test if a pandas object is empty, via the *empty* property.

```
In [51]: df.empty
Out[51]: False

In [52]: pd.DataFrame(columns=list("ABC")).empty
Out[52]: True
```

To evaluate single-element pandas objects in a boolean context, use the method *bool()*:

```
In [53]: pd.Series([True]).bool()
Out[53]: True

In [54]: pd.Series([False]).bool()
Out[54]: False

In [55]: pd.DataFrame([[True]]).bool()
Out[55]: True

In [56]: pd.DataFrame([[False]]).bool()
Out[56]: False
```

Warning: You might be tempted to do the following:

```
>>> if df:
...     pass
```

Or

```
>>> df and df2
```

These will both raise errors, as you are trying to compare multiple values.:

```
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.
↪all().
```

See *gotchas* for a more detailed discussion.

Comparing if objects are equivalent

Often you may find that there is more than one way to compute the same result. As a simple example, consider `df + df` and `df * 2`. To test that these two computations produce the same result, given the tools shown above, you might imagine using `(df + df == df * 2).all()`. But in fact, this expression is False:

```
In [57]: df + df == df * 2
Out[57]:
     one   two  three
a   True  True  False
b   True  True   True
c   True  True   True
d  False  True   True

In [58]: (df + df == df * 2).all()
Out[58]:
one      False
two       True
three    False
dtype: bool
```

Notice that the boolean DataFrame `df + df == df * 2` contains some False values! This is because NaNs do not compare as equals:

```
In [59]: np.nan == np.nan
Out[59]: False
```

So, NDFrames (such as Series and DataFrames) have an *`equals()`* method for testing equality, with NaNs in corresponding locations treated as equal.

```
In [60]: (df + df).equals(df * 2)
Out[60]: True
```

Note that the Series or DataFrame index needs to be in the same order for equality to be True:

```
In [61]: df1 = pd.DataFrame({"col": ["foo", 0, np.nan]})

In [62]: df2 = pd.DataFrame({"col": [np.nan, 0, "foo"]}, index=[2, 1, 0])

In [63]: df1.equals(df2)
Out[63]: False

In [64]: df1.equals(df2.sort_index())
Out[64]: True
```

Comparing array-like objects

You can conveniently perform element-wise comparisons when comparing a pandas data structure with a scalar value:

```
In [65]: pd.Series(["foo", "bar", "baz"]) == "foo"
Out[65]:
0     True
1    False
2    False
dtype: bool
```

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```
In [66]: pd.Index(["foo", "bar", "baz"]) == "foo"
Out[66]: array([ True, False, False])
```

pandas also handles element-wise comparisons between different array-like objects of the same length:

```
In [67]: pd.Series(["foo", "bar", "baz"]) == pd.Index(["foo", "bar", "qux"])
Out[67]:
0     True
1     True
2    False
dtype: bool

In [68]: pd.Series(["foo", "bar", "baz"]) == np.array(["foo", "bar", "qux"])
Out[68]:
0     True
1     True
2    False
dtype: bool
```

Trying to compare `Index` or `Series` objects of different lengths will raise a ValueError:

```
In [55]: pd.Series(['foo', 'bar', 'baz']) == pd.Series(['foo', 'bar'])
ValueError: Series lengths must match to compare

In [56]: pd.Series(['foo', 'bar', 'baz']) == pd.Series(['foo'])
ValueError: Series lengths must match to compare
```

Note that this is different from the NumPy behavior where a comparison can be broadcast:

```
In [69]: np.array([1, 2, 3]) == np.array([2])
Out[69]: array([False,  True, False])
```

or it can return False if broadcasting can not be done:

```
In [70]: np.array([1, 2, 3]) == np.array([1, 2])
Out[70]: False
```

Combining overlapping data sets

A problem occasionally arising is the combination of two similar data sets where values in one are preferred over the other. An example would be two data series representing a particular economic indicator where one is considered to be of "higher quality". However, the lower quality series might extend further back in history or have more complete data coverage. As such, we would like to combine two DataFrame objects where missing values in one DataFrame are conditionally filled with like-labeled values from the other DataFrame. The function implementing this operation is *combine_first()*, which we illustrate:

```
In [71]: df1 = pd.DataFrame(
   ....:     {"A": [1.0, np.nan, 3.0, 5.0, np.nan], "B": [np.nan, 2.0, 3.0, np.nan, 6.
↪0]}
   ....: )
   ....:

In [72]: df2 = pd.DataFrame(
   ....:     {
```

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```
   ....:         "A": [5.0, 2.0, 4.0, np.nan, 3.0, 7.0],
   ....:         "B": [np.nan, np.nan, 3.0, 4.0, 6.0, 8.0],
   ....:     }
   ....: )
   ....:

In [73]: df1
Out[73]:
     A    B
0  1.0  NaN
1  NaN  2.0
2  3.0  3.0
3  5.0  NaN
4  NaN  6.0

In [74]: df2
Out[74]:
     A    B
0  5.0  NaN
1  2.0  NaN
2  4.0  3.0
3  NaN  4.0
4  3.0  6.0
5  7.0  8.0

In [75]: df1.combine_first(df2)
Out[75]:
     A    B
0  1.0  NaN
1  2.0  2.0
2  3.0  3.0
3  5.0  4.0
4  3.0  6.0
5  7.0  8.0
```

General DataFrame combine

The *combine_first()* method above calls the more general *DataFrame.combine()*. This method takes another DataFrame and a combiner function, aligns the input DataFrame and then passes the combiner function pairs of Series (i.e., columns whose names are the same).

So, for instance, to reproduce *combine_first()* as above:

```
In [76]: def combiner(x, y):
   ....:     return np.where(pd.isna(x), y, x)
   ....:

In [77]: df1.combine(df2, combiner)
Out[77]:
     A    B
0  1.0  NaN
1  2.0  2.0
2  3.0  3.0
3  5.0  4.0
4  3.0  6.0
5  7.0  8.0
```

2.3.5 Descriptive statistics

There exists a large number of methods for computing descriptive statistics and other related operations on *Series*, *DataFrame*. Most of these are aggregations (hence producing a lower-dimensional result) like `sum()`, `mean()`, and `quantile()`, but some of them, like `cumsum()` and `cumprod()`, produce an object of the same size. Generally speaking, these methods take an **axis** argument, just like *ndarray.{sum, std, ...}*, but the axis can be specified by name or integer:

- **Series**: no axis argument needed
- **DataFrame**: "index" (axis=0, default), "columns" (axis=1)

For example:

```
In [78]: df
Out[78]:
        one       two     three
a  1.394981  1.772517       NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d       NaN  0.279344 -0.613172

In [79]: df.mean(0)
Out[79]:
one      0.811094
two      1.360588
three    0.187958
dtype: float64

In [80]: df.mean(1)
Out[80]:
a    1.583749
b    0.734929
c    1.133683
d   -0.166914
dtype: float64
```

All such methods have a `skipna` option signaling whether to exclude missing data (`True` by default):

```
In [81]: df.sum(0, skipna=False)
Out[81]:
one           NaN
two      5.442353
three         NaN
dtype: float64

In [82]: df.sum(axis=1, skipna=True)
Out[82]:
a    3.167498
b    2.204786
c    3.401050
d   -0.333828
dtype: float64
```

Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation of 1), very concisely:

```
In [83]: ts_stand = (df - df.mean()) / df.std()

In [84]: ts_stand.std()
Out[84]:
one      1.0
two      1.0
three    1.0
dtype: float64

In [85]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)

In [86]: xs_stand.std(1)
Out[86]:
a    1.0
b    1.0
c    1.0
d    1.0
dtype: float64
```

Note that methods like *cumsum()* and *cumprod()* preserve the location of NaN values. This is somewhat different from *expanding()* and *rolling()* since NaN behavior is furthermore dictated by a min_periods parameter.

```
In [87]: df.cumsum()
Out[87]:
        one       two     three
a  1.394981  1.772517       NaN
b  1.738035  3.684640 -0.050390
c  2.433281  5.163008  1.177045
d       NaN  5.442353  0.563873
```

Here is a quick reference summary table of common functions. Each also takes an optional level parameter which applies only if the object has a *hierarchical index*.

Function	Description
count	Number of non-NA observations
sum	Sum of values
mean	Mean of values
mad	Mean absolute deviation
median	Arithmetic median of values
min	Minimum
max	Maximum
mode	Mode
abs	Absolute Value
prod	Product of values
std	Bessel-corrected sample standard deviation
var	Unbiased variance
sem	Standard error of the mean
skew	Sample skewness (3rd moment)
kurt	Sample kurtosis (4th moment)
quantile	Sample quantile (value at %)
cumsum	Cumulative sum
cumprod	Cumulative product
cummax	Cumulative maximum
cummin	Cumulative minimum

Note that by chance some NumPy methods, like `mean`, `std`, and `sum`, will exclude NAs on Series input by default:

```
In [88]: np.mean(df["one"])
Out[88]: 0.8110935116651192

In [89]: np.mean(df["one"].to_numpy())
Out[89]: nan
```

`Series.nunique()` will return the number of unique non-NA values in a Series:

```
In [90]: series = pd.Series(np.random.randn(500))

In [91]: series[20:500] = np.nan

In [92]: series[10:20] = 5

In [93]: series.nunique()
Out[93]: 11
```

Summarizing data: describe

There is a convenient *`describe()`* function which computes a variety of summary statistics about a Series or the columns of a DataFrame (excluding NAs of course):

```
In [94]: series = pd.Series(np.random.randn(1000))

In [95]: series[::2] = np.nan

In [96]: series.describe()
Out[96]:
count    500.000000
mean      -0.021292
std        1.015906
min       -2.683763
25%       -0.699070
50%       -0.069718
75%        0.714483
max        3.160915
dtype: float64

In [97]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=["a", "b", "c", "d",
↪"e"])

In [98]: frame.iloc[::2] = np.nan

In [99]: frame.describe()
Out[99]:
                a           b           c           d           e
count  500.000000  500.000000  500.000000  500.000000  500.000000
mean     0.033387    0.030045   -0.043719   -0.051686    0.005979
std      1.017152    0.978743    1.025270    1.015988    1.006695
min     -3.000951   -2.637901   -3.303099   -3.159200   -3.188821
25%     -0.647623   -0.576449   -0.712369   -0.691338   -0.691115
50%      0.047578   -0.021499   -0.023888   -0.032652   -0.025363
75%      0.729907    0.775880    0.618896    0.670047    0.649748
max      2.740139    2.752332    3.004229    2.728702    3.240991
```

You can select specific percentiles to include in the output:

```
In [100]: series.describe(percentiles=[0.05, 0.25, 0.75, 0.95])
Out[100]:
count    500.000000
mean      -0.021292
std        1.015906
min       -2.683763
5%        -1.645423
25%       -0.699070
50%       -0.069718
75%        0.714483
95%        1.711409
max        3.160915
dtype: float64
```

By default, the median is always included.

For a non-numerical Series object, *describe()* will give a simple summary of the number of unique values and most frequently occurring values:

```
In [101]: s = pd.Series(["a", "a", "b", "b", "a", "a", np.nan, "c", "d", "a"])

In [102]: s.describe()
Out[102]:
count     9
unique    4
top       a
freq      5
dtype: object
```

Note that on a mixed-type DataFrame object, *describe()* will restrict the summary to include only numerical columns or, if none are, only categorical columns:

```
In [103]: frame = pd.DataFrame({"a": ["Yes", "Yes", "No", "No"], "b": range(4)})

In [104]: frame.describe()
Out[104]:
              b
count  4.000000
mean   1.500000
std    1.290994
min    0.000000
25%    0.750000
50%    1.500000
75%    2.250000
max    3.000000
```

This behavior can be controlled by providing a list of types as `include`/`exclude` arguments. The special value `all` can also be used:

```
In [105]: frame.describe(include=["object"])
Out[105]:
          a
count     4
unique    2
top      No
freq      2
```

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```
In [106]: frame.describe(include=["number"])
Out[106]:
              b
count  4.000000
mean   1.500000
std    1.290994
min    0.000000
25%    0.750000
50%    1.500000
75%    2.250000
max    3.000000

In [107]: frame.describe(include="all")
Out[107]:
          a         b
count     4  4.000000
unique    2       NaN
top      No       NaN
freq      2       NaN
mean    NaN  1.500000
std     NaN  1.290994
min     NaN  0.000000
25%     NaN  0.750000
50%     NaN  1.500000
75%     NaN  2.250000
max     NaN  3.000000
```

That feature relies on *select_dtypes*. Refer to there for details about accepted inputs.

Index of min/max values

The *idxmin()* and *idxmax()* functions on Series and DataFrame compute the index labels with the minimum and maximum corresponding values:

```
In [108]: s1 = pd.Series(np.random.randn(5))

In [109]: s1
Out[109]:
0    1.118076
1   -0.352051
2   -1.242883
3   -1.277155
4   -0.641184
dtype: float64

In [110]: s1.idxmin(), s1.idxmax()
Out[110]: (3, 0)

In [111]: df1 = pd.DataFrame(np.random.randn(5, 3), columns=["A", "B", "C"])

In [112]: df1
Out[112]:
          A         B         C
0 -0.327863 -0.946180 -0.137570
```

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```
1 -0.186235 -0.257213 -0.486567
2 -0.507027 -0.871259 -0.111110
3  2.000339 -2.430505  0.089759
4 -0.321434 -0.033695  0.096271

In [113]: df1.idxmin(axis=0)
Out[113]:
A    2
B    3
C    1
dtype: int64

In [114]: df1.idxmax(axis=1)
Out[114]:
0    C
1    A
2    C
3    A
4    C
dtype: object
```

When there are multiple rows (or columns) matching the minimum or maximum value, *idxmin()* and *idxmax()* return the first matching index:

```
In [115]: df3 = pd.DataFrame([2, 1, 1, 3, np.nan], columns=["A"], index=list("edcba"))

In [116]: df3
Out[116]:
     A
e  2.0
d  1.0
c  1.0
b  3.0
a  NaN

In [117]: df3["A"].idxmin()
Out[117]: 'd'
```

Note: `idxmin` and `idxmax` are called `argmin` and `argmax` in NumPy.

Value counts (histogramming) / mode

The *value_counts()* Series method and top-level function computes a histogram of a 1D array of values. It can also be used as a function on regular arrays:

```
In [118]: data = np.random.randint(0, 7, size=50)

In [119]: data
Out[119]:
array([6, 6, 2, 3, 5, 3, 2, 5, 4, 5, 4, 3, 4, 5, 0, 2, 0, 4, 2, 0, 3, 2,
       2, 5, 6, 5, 3, 4, 6, 4, 3, 5, 6, 4, 3, 6, 2, 6, 6, 2, 3, 4, 2, 1,
       6, 2, 6, 1, 5, 4])
```

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```
In [120]: s = pd.Series(data)

In [121]: s.value_counts()
Out[121]:
2    10
6    10
4     9
3     8
5     8
0     3
1     2
dtype: int64

In [122]: pd.value_counts(data)
Out[122]:
2    10
6    10
4     9
3     8
5     8
0     3
1     2
dtype: int64
```

New in version 1.1.0.

The *value_counts()* method can be used to count combinations across multiple columns. By default all columns are used but a subset can be selected using the `subset` argument.

```
In [123]: data = {"a": [1, 2, 3, 4], "b": ["x", "x", "y", "y"]}

In [124]: frame = pd.DataFrame(data)

In [125]: frame.value_counts()
Out[125]:
a  b
1  x    1
2  x    1
3  y    1
4  y    1
dtype: int64
```

Similarly, you can get the most frequently occurring value(s), i.e. the mode, of the values in a Series or DataFrame:

```
In [126]: s5 = pd.Series([1, 1, 3, 3, 3, 5, 5, 7, 7, 7])

In [127]: s5.mode()
Out[127]:
0    3
1    7
dtype: int64

In [128]: df5 = pd.DataFrame(
   .....:     {
   .....:         "A": np.random.randint(0, 7, size=50),
   .....:         "B": np.random.randint(-10, 15, size=50),
   .....:     }
```

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```
   .....: )
   .....:

In [129]: df5.mode()
Out[129]:
     A   B
0  1.0  -9
1  NaN  10
2  NaN  13
```

Discretization and quantiling

Continuous values can be discretized using the *cut()* (bins based on values) and *qcut()* (bins based on sample quantiles) functions:

```
In [130]: arr = np.random.randn(20)

In [131]: factor = pd.cut(arr, 4)

In [132]: factor
Out[132]:
[(-0.251, 0.464], (-0.968, -0.251], (0.464, 1.179], (-0.251, 0.464], (-0.968, -0.251],
↪ ..., (-0.251, 0.464], (-0.968, -0.251], (-0.968, -0.251], (-0.968, -0.251], (-0.
↪968, -0.251]]
Length: 20
Categories (4, interval[float64]): [(-0.968, -0.251] < (-0.251, 0.464] < (0.464, 1.
↪179] <
                                    (1.179, 1.893]]

In [133]: factor = pd.cut(arr, [-5, -1, 0, 1, 5])

In [134]: factor
Out[134]:
[(0, 1], (-1, 0], (0, 1], (0, 1], (-1, 0], ..., (-1, 0], (-1, 0], (-1, 0], (-1, 0], (-
↪1, 0]]
Length: 20
Categories (4, interval[int64]): [(-5, -1] < (-1, 0] < (0, 1] < (1, 5]]
```

qcut() computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quartiles like so:

```
In [135]: arr = np.random.randn(30)

In [136]: factor = pd.qcut(arr, [0, 0.25, 0.5, 0.75, 1])

In [137]: factor
Out[137]:
[(0.569, 1.184], (-2.278, -0.301], (-2.278, -0.301], (0.569, 1.184], (0.569, 1.184], .
↪.., (-0.301, 0.569], (1.184, 2.346], (1.184, 2.346], (-0.301, 0.569], (-2.278, -0.
↪301]]
Length: 30
Categories (4, interval[float64]): [(-2.278, -0.301] < (-0.301, 0.569] < (0.569, 1.
↪184] <
                                    (1.184, 2.346]]
```

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```
In [138]: pd.value_counts(factor)
Out[138]:
(-2.278, -0.301]    8
(1.184, 2.346]      8
(-0.301, 0.569]     7
(0.569, 1.184]      7
dtype: int64
```

We can also pass infinite values to define the bins:

```
In [139]: arr = np.random.randn(20)

In [140]: factor = pd.cut(arr, [-np.inf, 0, np.inf])

In [141]: factor
Out[141]:
[(-inf, 0.0], (0.0, inf], (0.0, inf], (-inf, 0.0], (-inf, 0.0], ..., (-inf, 0.0], (-
↪inf, 0.0], (-inf, 0.0], (0.0, inf], (0.0, inf]]
Length: 20
Categories (2, interval[float64]): [(-inf, 0.0] < (0.0, inf]]
```

2.3.6 Function application

To apply your own or another library's functions to pandas objects, you should be aware of the three methods below. The appropriate method to use depends on whether your function expects to operate on an entire `DataFrame` or `Series`, row- or column-wise, or elementwise.

1. *Tablewise Function Application*: `pipe()`
2. *Row or Column-wise Function Application*: `apply()`
3. *Aggregation API*: `agg()` and `transform()`
4. *Applying Elementwise Functions*: `applymap()`

Tablewise function application

`DataFrames` and `Series` can be passed into functions. However, if the function needs to be called in a chain, consider using the `pipe()` method.

First some setup:

```
In [142]: def extract_city_name(df):
   .....:     """
   .....:     Chicago, IL -> Chicago for city_name column
   .....:     """
   .....:     df["city_name"] = df["city_and_code"].str.split(",").str.get(0)
   .....:     return df
   .....:

In [143]: def add_country_name(df, country_name=None):
   .....:     """
   .....:     Chicago -> Chicago-US for city_name column
   .....:     """
   .....:     col = "city_name"
```

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```
   .....:     df["city_and_country"] = df[col] + country_name
   .....:     return df
   .....:

In [144]: df_p = pd.DataFrame({"city_and_code": ["Chicago, IL"]})
```

`extract_city_name` and `add_country_name` are functions taking and returning `DataFrames`.

Now compare the following:

```
In [145]: add_country_name(extract_city_name(df_p), country_name="US")
Out[145]:
  city_and_code city_name city_and_country
0   Chicago, IL   Chicago        ChicagoUS
```

Is equivalent to:

```
In [146]: df_p.pipe(extract_city_name).pipe(add_country_name, country_name="US")
Out[146]:
  city_and_code city_name city_and_country
0   Chicago, IL   Chicago        ChicagoUS
```

pandas encourages the second style, which is known as method chaining. `pipe` makes it easy to use your own or another library's functions in method chains, alongside pandas' methods.

In the example above, the functions `extract_city_name` and `add_country_name` each expected a `DataFrame` as the first positional argument. What if the function you wish to apply takes its data as, say, the second argument? In this case, provide `pipe` with a tuple of `(callable, data_keyword)`. `.pipe` will route the `DataFrame` to the argument specified in the tuple.

For example, we can fit a regression using statsmodels. Their API expects a formula first and a `DataFrame` as the second argument, `data`. We pass in the function, keyword pair `(sm.ols, 'data')` to `pipe`:

```
In [147]: import statsmodels.formula.api as sm

In [148]: bb = pd.read_csv("data/baseball.csv", index_col="id")

In [149]: (
   .....:     bb.query("h > 0")
   .....:     .assign(ln_h=lambda df: np.log(df.h))
   .....:     .pipe((sm.ols, "data"), "hr ~ ln_h + year + g + C(lg)")
   .....:     .fit()
   .....:     .summary()
   .....: )
   .....:
Out[149]:
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                     hr   R-squared:                       0.685
Model:                            OLS   Adj. R-squared:                  0.665
Method:                 Least Squares   F-statistic:                     34.28
Date:                Tue, 09 Feb 2021   Prob (F-statistic):           3.48e-15
Time:                        11:31:52   Log-Likelihood:                -205.92
No. Observations:                  68   AIC:                             421.8
Df Residuals:                      63   BIC:                             432.9
```

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```
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   -8484.7720   4664.146     -1.819      0.074   -1.78e+04     835.780
C(lg)[T.NL]    -2.2736      1.325     -1.716      0.091      -4.922       0.375
ln_h           -1.3542      0.875     -1.547      0.127      -3.103       0.395
year            4.2277      2.324      1.819      0.074      -0.417       8.872
g               0.1841      0.029      6.258      0.000       0.125       0.243
==============================================================================
Omnibus:                       10.875   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               17.298
Skew:                           0.537   Prob(JB):                     0.000175
Kurtosis:                       5.225   Cond. No.                     1.49e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly␣
↪specified.
[2] The condition number is large, 1.49e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

The pipe method is inspired by unix pipes and more recently dplyr and magrittr, which have introduced the popular `(%>%)` (read pipe) operator for R. The implementation of `pipe` here is quite clean and feels right at home in Python. We encourage you to view the source code of *`pipe()`*.

Row or column-wise function application

Arbitrary functions can be applied along the axes of a DataFrame using the *`apply()`* method, which, like the descriptive statistics methods, takes an optional `axis` argument:

```
In [150]: df.apply(np.mean)
Out[150]:
one      0.811094
two      1.360588
three    0.187958
dtype: float64

In [151]: df.apply(np.mean, axis=1)
Out[151]:
a    1.583749
b    0.734929
c    1.133683
d   -0.166914
dtype: float64

In [152]: df.apply(lambda x: x.max() - x.min())
Out[152]:
one      1.051928
two      1.632779
three    1.840607
dtype: float64
```

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```
In [153]: df.apply(np.cumsum)
Out[153]:
        one       two     three
a  1.394981  1.772517       NaN
b  1.738035  3.684640 -0.050390
c  2.433281  5.163008  1.177045
d       NaN  5.442353  0.563873

In [154]: df.apply(np.exp)
Out[154]:
        one       two     three
a  4.034899  5.885648       NaN
b  1.409244  6.767440  0.950858
c  2.004201  4.385785  3.412466
d       NaN  1.322262  0.541630
```

The *apply()* method will also dispatch on a string method name.

```
In [155]: df.apply("mean")
Out[155]:
one      0.811094
two      1.360588
three    0.187958
dtype: float64

In [156]: df.apply("mean", axis=1)
Out[156]:
a    1.583749
b    0.734929
c    1.133683
d   -0.166914
dtype: float64
```

The return type of the function passed to *apply()* affects the type of the final output from `DataFrame.apply` for the default behaviour:

- If the applied function returns a `Series`, the final output is a `DataFrame`. The columns match the index of the `Series` returned by the applied function.
- If the applied function returns any other type, the final output is a `Series`.

This default behaviour can be overridden using the `result_type`, which accepts three options: `reduce`, `broadcast`, and `expand`. These will determine how list-likes return values expand (or not) to a `DataFrame`.

apply() combined with some cleverness can be used to answer many questions about a data set. For example, suppose we wanted to extract the date where the maximum value for each column occurred:

```
In [157]: tsdf = pd.DataFrame(
   .....:     np.random.randn(1000, 3),
   .....:     columns=["A", "B", "C"],
   .....:     index=pd.date_range("1/1/2000", periods=1000),
   .....: )
   .....:

In [158]: tsdf.apply(lambda x: x.idxmax())
Out[158]:
A   2000-08-06
B   2001-01-18
```

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```
C   2001-07-18
dtype: datetime64[ns]
```

You may also pass additional arguments and keyword arguments to the *apply()* method. For instance, consider the following function you would like to apply:

```
def subtract_and_divide(x, sub, divide=1):
    return (x - sub) / divide
```

You may then apply this function as follows:

```
df.apply(subtract_and_divide, args=(5,), divide=3)
```

Another useful feature is the ability to pass Series methods to carry out some Series operation on each column or row:

```
In [159]: tsdf
Out[159]:
                   A         B         C
2000-01-01 -0.158131 -0.232466  0.321604
2000-01-02 -1.810340 -3.105758  0.433834
2000-01-03 -1.209847 -1.156793 -0.136794
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08 -0.653602  0.178875  1.008298
2000-01-09  1.007996  0.462824  0.254472
2000-01-10  0.307473  0.600337  1.643950

In [160]: tsdf.apply(pd.Series.interpolate)
Out[160]:
                   A         B         C
2000-01-01 -0.158131 -0.232466  0.321604
2000-01-02 -1.810340 -3.105758  0.433834
2000-01-03 -1.209847 -1.156793 -0.136794
2000-01-04 -1.098598 -0.889659  0.092225
2000-01-05 -0.987349 -0.622526  0.321243
2000-01-06 -0.876100 -0.355392  0.550262
2000-01-07 -0.764851 -0.088259  0.779280
2000-01-08 -0.653602  0.178875  1.008298
2000-01-09  1.007996  0.462824  0.254472
2000-01-10  0.307473  0.600337  1.643950
```

Finally, *apply()* takes an argument `raw` which is False by default, which converts each row or column into a Series before applying the function. When set to True, the passed function will instead receive an ndarray object, which has positive performance implications if you do not need the indexing functionality.

Aggregation API

The aggregation API allows one to express possibly multiple aggregation operations in a single concise way. This API is similar across pandas objects, see *groupby API*, the *window API*, and the *resample API*. The entry point for aggregation is `DataFrame.aggregate()`, or the alias `DataFrame.agg()`.

We will use a similar starting frame from above:

```
In [161]: tsdf = pd.DataFrame(
   .....:     np.random.randn(10, 3),
   .....:     columns=["A", "B", "C"],
   .....:     index=pd.date_range("1/1/2000", periods=10),
   .....: )
   .....:

In [162]: tsdf.iloc[3:7] = np.nan

In [163]: tsdf
Out[163]:
                   A         B         C
2000-01-01  1.257606  1.004194  0.167574
2000-01-02 -0.749892  0.288112 -0.757304
2000-01-03 -0.207550 -0.298599  0.116018
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.814347 -0.257623  0.869226
2000-01-09 -0.250663 -1.206601  0.896839
2000-01-10  2.169758 -1.333363  0.283157
```

Using a single function is equivalent to `apply()`. You can also pass named methods as strings. These will return a `Series` of the aggregated output:

```
In [164]: tsdf.agg(np.sum)
Out[164]:
A    3.033606
B   -1.803879
C    1.575510
dtype: float64

In [165]: tsdf.agg("sum")
Out[165]:
A    3.033606
B   -1.803879
C    1.575510
dtype: float64

# these are equivalent to a ``.sum()`` because we are aggregating
# on a single function
In [166]: tsdf.sum()
Out[166]:
A    3.033606
B   -1.803879
C    1.575510
dtype: float64
```

Single aggregations on a `Series` this will return a scalar value:

```
In [167]: tsdf["A"].agg("sum")
Out[167]: 3.033606102414146
```

Aggregating with multiple functions

You can pass multiple aggregation arguments as a list. The results of each of the passed functions will be a row in the resulting `DataFrame`. These are naturally named from the aggregation function.

```
In [168]: tsdf.agg(["sum"])
Out[168]:
            A         B        C
sum  3.033606 -1.803879  1.57551
```

Multiple functions yield multiple rows:

```
In [169]: tsdf.agg(["sum", "mean"])
Out[169]:
              A         B         C
sum    3.033606 -1.803879  1.575510
mean   0.505601 -0.300647  0.262585
```

On a `Series`, multiple functions return a `Series`, indexed by the function names:

```
In [170]: tsdf["A"].agg(["sum", "mean"])
Out[170]:
sum     3.033606
mean    0.505601
Name: A, dtype: float64
```

Passing a `lambda` function will yield a `<lambda>` named row:

```
In [171]: tsdf["A"].agg(["sum", lambda x: x.mean()])
Out[171]:
sum          3.033606
<lambda>     0.505601
Name: A, dtype: float64
```

Passing a named function will yield that name for the row:

```
In [172]: def mymean(x):
   .....:     return x.mean()
   .....:

In [173]: tsdf["A"].agg(["sum", mymean])
Out[173]:
sum       3.033606
mymean    0.505601
Name: A, dtype: float64
```

Aggregating with a dict

Passing a dictionary of column names to a scalar or a list of scalars, to `DataFrame.agg` allows you to customize which functions are applied to which columns. Note that the results are not in any particular order, you can use an `OrderedDict` instead to guarantee ordering.

```
In [174]: tsdf.agg({"A": "mean", "B": "sum"})
Out[174]:
A    0.505601
B   -1.803879
dtype: float64
```

Passing a list-like will generate a `DataFrame` output. You will get a matrix-like output of all of the aggregators. The output will consist of all unique functions. Those that are not noted for a particular column will be `NaN`:

```
In [175]: tsdf.agg({"A": ["mean", "min"], "B": "sum"})
Out[175]:
              A         B
mean   0.505601       NaN
min   -0.749892       NaN
sum         NaN -1.803879
```

Mixed dtypes

When presented with mixed dtypes that cannot aggregate, `.agg` will only take the valid aggregations. This is similar to how `.groupby.agg` works.

```
In [176]: mdf = pd.DataFrame(
   .....:     {
   .....:         "A": [1, 2, 3],
   .....:         "B": [1.0, 2.0, 3.0],
   .....:         "C": ["foo", "bar", "baz"],
   .....:         "D": pd.date_range("20130101", periods=3),
   .....:     }
   .....: )
   .....:

In [177]: mdf.dtypes
Out[177]:
A             int64
B           float64
C            object
D    datetime64[ns]
dtype: object
```

```
In [178]: mdf.agg(["min", "sum"])
Out[178]:
     A    B          C          D
min  1  1.0        bar 2013-01-01
sum  6  6.0  foobarbaz        NaT
```

Custom describe

With `.agg()` it is possible to easily create a custom describe function, similar to the built in *describe function*.

```
In [179]: from functools import partial

In [180]: q_25 = partial(pd.Series.quantile, q=0.25)

In [181]: q_25.__name__ = "25%"

In [182]: q_75 = partial(pd.Series.quantile, q=0.75)

In [183]: q_75.__name__ = "75%"

In [184]: tsdf.agg(["count", "mean", "std", "min", q_25, "median", q_75, "max"])
Out[184]:
                A         B         C
count    6.000000  6.000000  6.000000
mean     0.505601 -0.300647  0.262585
std      1.103362  0.887508  0.606860
min     -0.749892 -1.333363 -0.757304
25%     -0.239885 -0.979600  0.128907
median   0.303398 -0.278111  0.225365
75%      1.146791  0.151678  0.722709
max      2.169758  1.004194  0.896839
```

Transform API

The *`transform()`* method returns an object that is indexed the same (same size) as the original. This API allows you to provide *multiple* operations at the same time rather than one-by-one. Its API is quite similar to the `.agg` API.

We create a frame similar to the one used in the above sections.

```
In [185]: tsdf = pd.DataFrame(
   .....:     np.random.randn(10, 3),
   .....:     columns=["A", "B", "C"],
   .....:     index=pd.date_range("1/1/2000", periods=10),
   .....: )
   .....:

In [186]: tsdf.iloc[3:7] = np.nan

In [187]: tsdf
Out[187]:
                   A         B         C
2000-01-01 -0.428759 -0.864890 -0.675341
2000-01-02 -0.168731  1.338144 -1.279321
2000-01-03 -1.621034  0.438107  0.903794
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.254374 -1.240447 -0.201052
2000-01-09 -0.157795  0.791197 -1.144209
2000-01-10 -0.030876  0.371900  0.061932
```

Transform the entire frame. `.transform()` allows input functions as: a NumPy function, a string function name or a user defined function.

```
In [188]: tsdf.transform(np.abs)
Out[188]:
                   A         B         C
2000-01-01  0.428759  0.864890  0.675341
2000-01-02  0.168731  1.338144  1.279321
2000-01-03  1.621034  0.438107  0.903794
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.254374  1.240447  0.201052
2000-01-09  0.157795  0.791197  1.144209
2000-01-10  0.030876  0.371900  0.061932

In [189]: tsdf.transform("abs")
Out[189]:
                   A         B         C
2000-01-01  0.428759  0.864890  0.675341
2000-01-02  0.168731  1.338144  1.279321
2000-01-03  1.621034  0.438107  0.903794
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.254374  1.240447  0.201052
2000-01-09  0.157795  0.791197  1.144209
2000-01-10  0.030876  0.371900  0.061932

In [190]: tsdf.transform(lambda x: x.abs())
Out[190]:
                   A         B         C
2000-01-01  0.428759  0.864890  0.675341
2000-01-02  0.168731  1.338144  1.279321
2000-01-03  1.621034  0.438107  0.903794
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.254374  1.240447  0.201052
2000-01-09  0.157795  0.791197  1.144209
2000-01-10  0.030876  0.371900  0.061932
```

Here *`transform()`* received a single function; this is equivalent to a ufunc application.

```
In [191]: np.abs(tsdf)
Out[191]:
                   A         B         C
2000-01-01  0.428759  0.864890  0.675341
2000-01-02  0.168731  1.338144  1.279321
2000-01-03  1.621034  0.438107  0.903794
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.254374  1.240447  0.201052
```

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```
2000-01-09  0.157795  0.791197  1.144209
2000-01-10  0.030876  0.371900  0.061932
```

Passing a single function to `.transform()` with a `Series` will yield a single `Series` in return.

```
In [192]: tsdf["A"].transform(np.abs)
Out[192]:
2000-01-01    0.428759
2000-01-02    0.168731
2000-01-03    1.621034
2000-01-04         NaN
2000-01-05         NaN
2000-01-06         NaN
2000-01-07         NaN
2000-01-08    0.254374
2000-01-09    0.157795
2000-01-10    0.030876
Freq: D, Name: A, dtype: float64
```

Transform with multiple functions

Passing multiple functions will yield a column MultiIndexed DataFrame. The first level will be the original frame column names; the second level will be the names of the transforming functions.

```
In [193]: tsdf.transform([np.abs, lambda x: x + 1])
Out[193]:
                   A                   B                   C
            absolute  <lambda>  absolute  <lambda>  absolute  <lambda>
2000-01-01  0.428759  0.571241  0.864890  0.135110  0.675341  0.324659
2000-01-02  0.168731  0.831269  1.338144  2.338144  1.279321 -0.279321
2000-01-03  1.621034 -0.621034  0.438107  1.438107  0.903794  1.903794
2000-01-04       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-08  0.254374  1.254374  1.240447 -0.240447  0.201052  0.798948
2000-01-09  0.157795  0.842205  0.791197  1.791197  1.144209 -0.144209
2000-01-10  0.030876  0.969124  0.371900  1.371900  0.061932  1.061932
```

Passing multiple functions to a Series will yield a DataFrame. The resulting column names will be the transforming functions.

```
In [194]: tsdf["A"].transform([np.abs, lambda x: x + 1])
Out[194]:
            absolute  <lambda>
2000-01-01  0.428759  0.571241
2000-01-02  0.168731  0.831269
2000-01-03  1.621034 -0.621034
2000-01-04       NaN       NaN
2000-01-05       NaN       NaN
2000-01-06       NaN       NaN
2000-01-07       NaN       NaN
2000-01-08  0.254374  1.254374
2000-01-09  0.157795  0.842205
2000-01-10  0.030876  0.969124
```

Transforming with a dict

Passing a dict of functions will allow selective transforming per column.

```
In [195]: tsdf.transform({"A": np.abs, "B": lambda x: x + 1})
Out[195]:
                   A         B
2000-01-01  0.428759  0.135110
2000-01-02  0.168731  2.338144
2000-01-03  1.621034  1.438107
2000-01-04       NaN       NaN
2000-01-05       NaN       NaN
2000-01-06       NaN       NaN
2000-01-07       NaN       NaN
2000-01-08  0.254374 -0.240447
2000-01-09  0.157795  1.791197
2000-01-10  0.030876  1.371900
```

Passing a dict of lists will generate a MultiIndexed DataFrame with these selective transforms.

```
In [196]: tsdf.transform({"A": np.abs, "B": [lambda x: x + 1, "sqrt"]})
Out[196]:
                   A         B
                   A  <lambda>      sqrt
2000-01-01  0.428759  0.135110       NaN
2000-01-02  0.168731  2.338144  1.156782
2000-01-03  1.621034  1.438107  0.661897
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.254374 -0.240447       NaN
2000-01-09  0.157795  1.791197  0.889493
2000-01-10  0.030876  1.371900  0.609836
```

Applying elementwise functions

Since not all functions can be vectorized (accept NumPy arrays and return another array or value), the methods *applymap()* on DataFrame and analogously *map()* on Series accept any Python function taking a single value and returning a single value. For example:

```
In [197]: df4
Out[197]:
        one       two     three
a  1.394981  1.772517       NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d       NaN  0.279344 -0.613172

In [198]: def f(x):
   .....:     return len(str(x))
   .....:

In [199]: df4["one"].map(f)
Out[199]:
a    18
```

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```
b    19
c    18
d     3
Name: one, dtype: int64

In [200]: df4.applymap(f)
Out[200]:
   one  two  three
a   18   17      3
b   19   18     20
c   18   18     16
d    3   19     19
```

Series.map() has an additional feature; it can be used to easily "link" or "map" values defined by a secondary series. This is closely related to *merging/joining functionality*:

```
In [201]: s = pd.Series(
   .....:     ["six", "seven", "six", "seven", "six"], index=["a", "b", "c", "d", "e"]
   .....: )
   .....:

In [202]: t = pd.Series({"six": 6.0, "seven": 7.0})

In [203]: s
Out[203]:
a      six
b    seven
c      six
d    seven
e      six
dtype: object

In [204]: s.map(t)
Out[204]:
a    6.0
b    7.0
c    6.0
d    7.0
e    6.0
dtype: float64
```

2.3.7 Reindexing and altering labels

reindex() is the fundamental data alignment method in pandas. It is used to implement nearly all other features relying on label-alignment functionality. To *reindex* means to conform the data to match a given set of labels along a particular axis. This accomplishes several things:

- Reorders the existing data to match a new set of labels
- Inserts missing value (NA) markers in label locations where no data for that label existed
- If specified, **fill** data for missing labels using logic (highly relevant to working with time series data)

Here is a simple example:

```
In [205]: s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])

In [206]: s
Out[206]:
a    1.695148
b    1.328614
c    1.234686
d   -0.385845
e   -1.326508
dtype: float64

In [207]: s.reindex(["e", "b", "f", "d"])
Out[207]:
e   -1.326508
b    1.328614
f         NaN
d   -0.385845
dtype: float64
```

Here, the `f` label was not contained in the Series and hence appears as `NaN` in the result.

With a DataFrame, you can simultaneously reindex the index and columns:

```
In [208]: df
Out[208]:
        one       two     three
a  1.394981  1.772517       NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d       NaN  0.279344 -0.613172

In [209]: df.reindex(index=["c", "f", "b"], columns=["three", "two", "one"])
Out[209]:
      three       two       one
c  1.227435  1.478369  0.695246
f       NaN       NaN       NaN
b -0.050390  1.912123  0.343054
```

You may also use `reindex` with an `axis` keyword:

```
In [210]: df.reindex(["c", "f", "b"], axis="index")
Out[210]:
        one       two     three
c  0.695246  1.478369  1.227435
f       NaN       NaN       NaN
b  0.343054  1.912123 -0.050390
```

Note that the `Index` objects containing the actual axis labels can be **shared** between objects. So if we have a Series and a DataFrame, the following can be done:

```
In [211]: rs = s.reindex(df.index)

In [212]: rs
Out[212]:
a    1.695148
b    1.328614
c    1.234686
d   -0.385845
```

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```
dtype: float64

In [213]: rs.index is df.index
Out[213]: True
```

This means that the reindexed Series's index is the same Python object as the DataFrame's index.

DataFrame.reindex() also supports an "axis-style" calling convention, where you specify a single `labels` argument and the `axis` it applies to.

```
In [214]: df.reindex(["c", "f", "b"], axis="index")
Out[214]:
        one       two     three
c  0.695246  1.478369  1.227435
f       NaN       NaN       NaN
b  0.343054  1.912123 -0.050390

In [215]: df.reindex(["three", "two", "one"], axis="columns")
Out[215]:
      three       two       one
a       NaN  1.772517  1.394981
b -0.050390  1.912123  0.343054
c  1.227435  1.478369  0.695246
d -0.613172  0.279344       NaN
```

See also:

MultiIndex / Advanced Indexing is an even more concise way of doing reindexing.

Note: When writing performance-sensitive code, there is a good reason to spend some time becoming a reindexing ninja: **many operations are faster on pre-aligned data**. Adding two unaligned DataFrames internally triggers a reindexing step. For exploratory analysis you will hardly notice the difference (because `reindex` has been heavily optimized), but when CPU cycles matter sprinkling a few explicit `reindex` calls here and there can have an impact.

Reindexing to align with another object

You may wish to take an object and reindex its axes to be labeled the same as another object. While the syntax for this is straightforward albeit verbose, it is a common enough operation that the *reindex_like()* method is available to make this simpler:

```
In [216]: df2
Out[216]:
        one       two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369

In [217]: df3
Out[217]:
        one       two
a  0.583888  0.051514
b -0.468040  0.191120
c -0.115848 -0.242634
```

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```
In [218]: df.reindex_like(df2)
Out[218]:
        one       two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369
```

Aligning objects with each other with `align`

The *`align()`* method is the fastest way to simultaneously align two objects. It supports a `join` argument (related to *joining and merging*):

- `join='outer'`: take the union of the indexes (default)
- `join='left'`: use the calling object's index
- `join='right'`: use the passed object's index
- `join='inner'`: intersect the indexes

It returns a tuple with both of the reindexed Series:

```
In [219]: s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])

In [220]: s1 = s[:4]

In [221]: s2 = s[1:]

In [222]: s1.align(s2)
Out[222]:
(a   -0.186646
 b   -1.692424
 c   -0.303893
 d   -1.425662
 e         NaN
 dtype: float64,
 a         NaN
 b   -1.692424
 c   -0.303893
 d   -1.425662
 e    1.114285
 dtype: float64)

In [223]: s1.align(s2, join="inner")
Out[223]:
(b   -1.692424
 c   -0.303893
 d   -1.425662
 dtype: float64,
 b   -1.692424
 c   -0.303893
 d   -1.425662
 dtype: float64)

In [224]: s1.align(s2, join="left")
Out[224]:
(a   -0.186646
```

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```
b   -1.692424
c   -0.303893
d   -1.425662
dtype: float64,
a         NaN
b   -1.692424
c   -0.303893
d   -1.425662
dtype: float64)
```

For DataFrames, the join method will be applied to both the index and the columns by default:

```
In [225]: df.align(df2, join="inner")
Out[225]:
(        one       two
 a  1.394981  1.772517
 b  0.343054  1.912123
 c  0.695246  1.478369,
         one       two
 a  1.394981  1.772517
 b  0.343054  1.912123
 c  0.695246  1.478369)
```

You can also pass an `axis` option to only align on the specified axis:

```
In [226]: df.align(df2, join="inner", axis=0)
Out[226]:
(        one       two     three
 a  1.394981  1.772517       NaN
 b  0.343054  1.912123 -0.050390
 c  0.695246  1.478369  1.227435,
         one       two
 a  1.394981  1.772517
 b  0.343054  1.912123
 c  0.695246  1.478369)
```

If you pass a Series to *DataFrame.align()*, you can choose to align both objects either on the DataFrame's index or columns using the `axis` argument:

```
In [227]: df.align(df2.iloc[0], axis=1)
Out[227]:
(        one     three       two
 a  1.394981       NaN  1.772517
 b  0.343054 -0.050390  1.912123
 c  0.695246  1.227435  1.478369
 d       NaN -0.613172  0.279344,
 one      1.394981
 three         NaN
 two      1.772517
 Name: a, dtype: float64)
```

Filling while reindexing

reindex() takes an optional parameter `method` which is a filling method chosen from the following table:

Method	Action
pad / ffill	Fill values forward
bfill / backfill	Fill values backward
nearest	Fill from the nearest index value

We illustrate these fill methods on a simple Series:

```
In [228]: rng = pd.date_range("1/3/2000", periods=8)

In [229]: ts = pd.Series(np.random.randn(8), index=rng)

In [230]: ts2 = ts[[0, 3, 6]]

In [231]: ts
Out[231]:
2000-01-03    0.183051
2000-01-04    0.400528
2000-01-05   -0.015083
2000-01-06    2.395489
2000-01-07    1.414806
2000-01-08    0.118428
2000-01-09    0.733639
2000-01-10   -0.936077
Freq: D, dtype: float64

In [232]: ts2
Out[232]:
2000-01-03    0.183051
2000-01-06    2.395489
2000-01-09    0.733639
Freq: 3D, dtype: float64

In [233]: ts2.reindex(ts.index)
Out[233]:
2000-01-03    0.183051
2000-01-04         NaN
2000-01-05         NaN
2000-01-06    2.395489
2000-01-07         NaN
2000-01-08         NaN
2000-01-09    0.733639
2000-01-10         NaN
Freq: D, dtype: float64

In [234]: ts2.reindex(ts.index, method="ffill")
Out[234]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05    0.183051
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08    2.395489
2000-01-09    0.733639
```

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```
2000-01-10    0.733639
Freq: D, dtype: float64

In [235]: ts2.reindex(ts.index, method="bfill")
Out[235]:
2000-01-03    0.183051
2000-01-04    2.395489
2000-01-05    2.395489
2000-01-06    2.395489
2000-01-07    0.733639
2000-01-08    0.733639
2000-01-09    0.733639
2000-01-10         NaN
Freq: D, dtype: float64

In [236]: ts2.reindex(ts.index, method="nearest")
Out[236]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05    2.395489
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08    0.733639
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

These methods require that the indexes are **ordered** increasing or decreasing.

Note that the same result could have been achieved using *fillna* (except for `method='nearest'`) or *interpolate*:

```
In [237]: ts2.reindex(ts.index).fillna(method="ffill")
Out[237]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05    0.183051
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08    2.395489
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

reindex() will raise a ValueError if the index is not monotonically increasing or decreasing. *fillna()* and *interpolate()* will not perform any checks on the order of the index.

Limits on filling while reindexing

The `limit` and `tolerance` arguments provide additional control over filling while reindexing. Limit specifies the maximum count of consecutive matches:

```
In [238]: ts2.reindex(ts.index, method="ffill", limit=1)
Out[238]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05         NaN
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08         NaN
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

In contrast, tolerance specifies the maximum distance between the index and indexer values:

```
In [239]: ts2.reindex(ts.index, method="ffill", tolerance="1 day")
Out[239]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05         NaN
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08         NaN
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

Notice that when used on a `DatetimeIndex`, `TimedeltaIndex` or `PeriodIndex`, `tolerance` will coerced into a `Timedelta` if possible. This allows you to specify tolerance with appropriate strings.

Dropping labels from an axis

A method closely related to `reindex` is the *`drop()`* function. It removes a set of labels from an axis:

```
In [240]: df
Out[240]:
        one       two     three
a  1.394981  1.772517       NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d       NaN  0.279344 -0.613172

In [241]: df.drop(["a", "d"], axis=0)
Out[241]:
        one       two     three
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435

In [242]: df.drop(["one"], axis=1)
Out[242]:
        two     three
a  1.772517       NaN
```

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```
b  1.912123 -0.050390
c  1.478369  1.227435
d  0.279344 -0.613172
```

Note that the following also works, but is a bit less obvious / clean:

```
In [243]: df.reindex(df.index.difference(["a", "d"]))
Out[243]:
        one       two     three
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
```

Renaming / mapping labels

The *rename()* method allows you to relabel an axis based on some mapping (a dict or Series) or an arbitrary function.

```
In [244]: s
Out[244]:
a   -0.186646
b   -1.692424
c   -0.303893
d   -1.425662
e    1.114285
dtype: float64

In [245]: s.rename(str.upper)
Out[245]:
A   -0.186646
B   -1.692424
C   -0.303893
D   -1.425662
E    1.114285
dtype: float64
```

If you pass a function, it must return a value when called with any of the labels (and must produce a set of unique values). A dict or Series can also be used:

```
In [246]: df.rename(
   .....:     columns={"one": "foo", "two": "bar"},
   .....:     index={"a": "apple", "b": "banana", "d": "durian"},
   .....: )
   .....:
Out[246]:
              foo       bar     three
apple    1.394981  1.772517       NaN
banana   0.343054  1.912123 -0.050390
c        0.695246  1.478369  1.227435
durian        NaN  0.279344 -0.613172
```

If the mapping doesn't include a column/index label, it isn't renamed. Note that extra labels in the mapping don't throw an error.

DataFrame.rename() also supports an "axis-style" calling convention, where you specify a single `mapper` and the `axis` to apply that mapping to.

```
In [247]: df.rename({"one": "foo", "two": "bar"}, axis="columns")
Out[247]:
        foo       bar     three
a  1.394981  1.772517       NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d       NaN  0.279344 -0.613172

In [248]: df.rename({"a": "apple", "b": "banana", "d": "durian"}, axis="index")
Out[248]:
             one       two     three
apple   1.394981  1.772517       NaN
banana  0.343054  1.912123 -0.050390
c       0.695246  1.478369  1.227435
durian       NaN  0.279344 -0.613172
```

The *rename()* method also provides an `inplace` named parameter that is by default `False` and copies the underlying data. Pass `inplace=True` to rename the data in place.

Finally, *rename()* also accepts a scalar or list-like for altering the `Series.name` attribute.

```
In [249]: s.rename("scalar-name")
Out[249]:
a   -0.186646
b   -1.692424
c   -0.303893
d   -1.425662
e    1.114285
Name: scalar-name, dtype: float64
```

New in version 0.24.0.

The methods *DataFrame.rename_axis()* and *Series.rename_axis()* allow specific names of a `MultiIndex` to be changed (as opposed to the labels).

```
In [250]: df = pd.DataFrame(
   .....:     {"x": [1, 2, 3, 4, 5, 6], "y": [10, 20, 30, 40, 50, 60]},
   .....:     index=pd.MultiIndex.from_product(
   .....:         [["a", "b", "c"], [1, 2]], names=["let", "num"]
   .....:     ),
   .....: )
   .....:

In [251]: df
Out[251]:
         x   y
let num
a   1    1  10
    2    2  20
b   1    3  30
    2    4  40
c   1    5  50
    2    6  60

In [252]: df.rename_axis(index={"let": "abc"})
Out[252]:
         x   y
abc num
```

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```
a   1    1  10
    2    2  20
b   1    3  30
    2    4  40
c   1    5  50
    2    6  60

In [253]: df.rename_axis(index=str.upper)
Out[253]:
          x   y
LET NUM
a   1     1  10
    2     2  20
b   1     3  30
    2     4  40
c   1     5  50
    2     6  60
```

2.3.8 Iteration

The behavior of basic iteration over pandas objects depends on the type. When iterating over a Series, it is regarded as array-like, and basic iteration produces the values. DataFrames follow the dict-like convention of iterating over the "keys" of the objects.

In short, basic iteration (`for i in object`) produces:

- **Series**: values
- **DataFrame**: column labels

Thus, for example, iterating over a DataFrame gives you the column names:

```
In [254]: df = pd.DataFrame(
   .....:     {"col1": np.random.randn(3), "col2": np.random.randn(3)}, index=["a", "b
↪", "c"]
   .....: )
   .....:

In [255]: for col in df:
   .....:     print(col)
   .....:
col1
col2
```

pandas objects also have the dict-like *items()* method to iterate over the (key, value) pairs.

To iterate over the rows of a DataFrame, you can use the following methods:

- *iterrows()*: Iterate over the rows of a DataFrame as (index, Series) pairs. This converts the rows to Series objects, which can change the dtypes and has some performance implications.
- *itertuples()*: Iterate over the rows of a DataFrame as namedtuples of the values. This is a lot faster than *iterrows()*, and is in most cases preferable to use to iterate over the values of a DataFrame.

Warning: Iterating through pandas objects is generally **slow**. In many cases, iterating manually over the rows is not needed and can be avoided with one of the following approaches:

- Look for a *vectorized* solution: many operations can be performed using built-in methods or NumPy functions, (boolean) indexing, ...
- When you have a function that cannot work on the full DataFrame/Series at once, it is better to use `apply()` instead of iterating over the values. See the docs on *function application*.
- If you need to do iterative manipulations on the values but performance is important, consider writing the inner loop with cython or numba. See the *enhancing performance* section for some examples of this approach.

Warning: You should **never modify** something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect!

For example, in the following case setting the value has no effect:

```
In [256]: df = pd.DataFrame({"a": [1, 2, 3], "b": ["a", "b", "c"]})

In [257]: for index, row in df.iterrows():
   .....:     row["a"] = 10
   .....:

In [258]: df
Out[258]:
   a  b
0  1  a
1  2  b
2  3  c
```

items

Consistent with the dict-like interface, `items()` iterates through key-value pairs:

- **Series**: (index, scalar value) pairs
- **DataFrame**: (column, Series) pairs

For example:

```
In [259]: for label, ser in df.items():
   .....:     print(label)
   .....:     print(ser)
   .....:
a
0    1
1    2
2    3
Name: a, dtype: int64
b
0    a
1    b
2    c
Name: b, dtype: object
```

iterrows

iterrows() allows you to iterate through the rows of a DataFrame as Series objects. It returns an iterator yielding each index value along with a Series containing the data in each row:

```
In [260]: for row_index, row in df.iterrows():
   .....:     print(row_index, row, sep="\n")
   .....:
0
a    1
b    a
Name: 0, dtype: object
1
a    2
b    b
Name: 1, dtype: object
2
a    3
b    c
Name: 2, dtype: object
```

Note: Because *iterrows()* returns a Series for each row, it does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
In [261]: df_orig = pd.DataFrame([[1, 1.5]], columns=["int", "float"])

In [262]: df_orig.dtypes
Out[262]:
int        int64
float    float64
dtype: object

In [263]: row = next(df_orig.iterrows())[1]

In [264]: row
Out[264]:
int      1.0
float    1.5
Name: 0, dtype: float64
```

All values in `row`, returned as a Series, are now upcasted to floats, also the original integer value in column `x`:

```
In [265]: row["int"].dtype
Out[265]: dtype('float64')

In [266]: df_orig["int"].dtype
Out[266]: dtype('int64')
```

To preserve dtypes while iterating over the rows, it is better to use *itertuples()* which returns namedtuples of the values and which is generally much faster than *iterrows()*.

For instance, a contrived way to transpose the DataFrame would be:

```
In [267]: df2 = pd.DataFrame({"x": [1, 2, 3], "y": [4, 5, 6]})

In [268]: print(df2)
```

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```
   x  y
0  1  4
1  2  5
2  3  6

In [269]: print(df2.T)
   0  1  2
x  1  2  3
y  4  5  6

In [270]: df2_t = pd.DataFrame({idx: values for idx, values in df2.iterrows()})

In [271]: print(df2_t)
   0  1  2
x  1  2  3
y  4  5  6
```

itertuples

The *itertuples()* method will return an iterator yielding a namedtuple for each row in the DataFrame. The first element of the tuple will be the row's corresponding index value, while the remaining values are the row values.

For instance:

```
In [272]: for row in df.itertuples():
   .....:     print(row)
   .....:
Pandas(Index=0, a=1, b='a')
Pandas(Index=1, a=2, b='b')
Pandas(Index=2, a=3, b='c')
```

This method does not convert the row to a Series object; it merely returns the values inside a namedtuple. Therefore, *itertuples()* preserves the data type of the values and is generally faster as *iterrows()*.

Note: The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. With a large number of columns (>255), regular tuples are returned.

2.3.9 .dt accessor

`Series` has an accessor to succinctly return datetime like properties for the *values* of the Series, if it is a datetime/period like Series. This will return a Series, indexed like the existing Series.

```
# datetime
In [273]: s = pd.Series(pd.date_range("20130101 09:10:12", periods=4))

In [274]: s
Out[274]:
0   2013-01-01 09:10:12
1   2013-01-02 09:10:12
2   2013-01-03 09:10:12
3   2013-01-04 09:10:12
dtype: datetime64[ns]
```

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```
In [275]: s.dt.hour
Out[275]:
0    9
1    9
2    9
3    9
dtype: int64

In [276]: s.dt.second
Out[276]:
0    12
1    12
2    12
3    12
dtype: int64

In [277]: s.dt.day
Out[277]:
0    1
1    2
2    3
3    4
dtype: int64
```

This enables nice expressions like this:

```
In [278]: s[s.dt.day == 2]
Out[278]:
1   2013-01-02 09:10:12
dtype: datetime64[ns]
```

You can easily produces tz aware transformations:

```
In [279]: stz = s.dt.tz_localize("US/Eastern")

In [280]: stz
Out[280]:
0   2013-01-01 09:10:12-05:00
1   2013-01-02 09:10:12-05:00
2   2013-01-03 09:10:12-05:00
3   2013-01-04 09:10:12-05:00
dtype: datetime64[ns, US/Eastern]

In [281]: stz.dt.tz
Out[281]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [282]: s.dt.tz_localize("UTC").dt.tz_convert("US/Eastern")
Out[282]:
0   2013-01-01 04:10:12-05:00
1   2013-01-02 04:10:12-05:00
2   2013-01-03 04:10:12-05:00
3   2013-01-04 04:10:12-05:00
dtype: datetime64[ns, US/Eastern]
```

You can also format datetime values as strings with *Series.dt.strftime()* which supports the same format as the standard strftime().

```
# DatetimeIndex
In [283]: s = pd.Series(pd.date_range("20130101", periods=4))

In [284]: s
Out[284]:
0   2013-01-01
1   2013-01-02
2   2013-01-03
3   2013-01-04
dtype: datetime64[ns]

In [285]: s.dt.strftime("%Y/%m/%d")
Out[285]:
0    2013/01/01
1    2013/01/02
2    2013/01/03
3    2013/01/04
dtype: object
```

```
# PeriodIndex
In [286]: s = pd.Series(pd.period_range("20130101", periods=4))

In [287]: s
Out[287]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
dtype: period[D]

In [288]: s.dt.strftime("%Y/%m/%d")
Out[288]:
0    2013/01/01
1    2013/01/02
2    2013/01/03
3    2013/01/04
dtype: object
```

The .dt accessor works for period and timedelta dtypes.

```
# period
In [289]: s = pd.Series(pd.period_range("20130101", periods=4, freq="D"))

In [290]: s
Out[290]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
dtype: period[D]

In [291]: s.dt.year
Out[291]:
0    2013
1    2013
```

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```
2    2013
3    2013
dtype: int64

In [292]: s.dt.day
Out[292]:
0    1
1    2
2    3
3    4
dtype: int64
```

```
# timedelta
In [293]: s = pd.Series(pd.timedelta_range("1 day 00:00:05", periods=4, freq="s"))

In [294]: s
Out[294]:
0   1 days 00:00:05
1   1 days 00:00:06
2   1 days 00:00:07
3   1 days 00:00:08
dtype: timedelta64[ns]

In [295]: s.dt.days
Out[295]:
0    1
1    1
2    1
3    1
dtype: int64

In [296]: s.dt.seconds
Out[296]:
0    5
1    6
2    7
3    8
dtype: int64

In [297]: s.dt.components
Out[297]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0     1      0        0        5             0             0            0
1     1      0        0        6             0             0            0
2     1      0        0        7             0             0            0
3     1      0        0        8             0             0            0
```

Note: `Series.dt` will raise a `TypeError` if you access with a non-datetime-like values.

2.3.10 Vectorized string methods

Series is equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the Series's `str` attribute and generally have names matching the equivalent (scalar) built-in string methods. For example:

```
In [298]: s = pd.Series(
   .....:     ["A", "B", "C", "Aaba", "Baca", np.nan, "CABA", "dog", "cat"],␣
↪dtype="string"
   .....: )
   .....:

In [299]: s.str.lower()
Out[299]:
0       a
1       b
2       c
3    aaba
4    baca
5    <NA>
6    caba
7     dog
8     cat
dtype: string
```

Powerful pattern-matching methods are provided as well, but note that pattern-matching generally uses regular expressions by default (and in some cases always uses them).

Note: Prior to pandas 1.0, string methods were only available on `object` -dtype `Series`. pandas 1.0 added the *`StringDtype`* which is dedicated to strings. See *Text data types* for more.

Please see *Vectorized String Methods* for a complete description.

2.3.11 Sorting

pandas supports three kinds of sorting: sorting by index labels, sorting by column values, and sorting by a combination of both.

By index

The *`Series.sort_index()`* and *`DataFrame.sort_index()`* methods are used to sort a pandas object by its index levels.

```
In [300]: df = pd.DataFrame(
   .....:     {
   .....:         "one": pd.Series(np.random.randn(3), index=["a", "b", "c"]),
   .....:         "two": pd.Series(np.random.randn(4), index=["a", "b", "c", "d"]),
   .....:         "three": pd.Series(np.random.randn(3), index=["b", "c", "d"]),
   .....:     }
   .....: )
   .....:

In [301]: unsorted_df = df.reindex(
```

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```
   .....:     index=["a", "d", "c", "b"], columns=["three", "two", "one"]
   .....: )
   .....:

In [302]: unsorted_df
Out[302]:
      three       two       one
a       NaN -1.152244  0.562973
d -0.252916 -0.109597       NaN
c  1.273388 -0.167123  0.640382
b -0.098217  0.009797 -1.299504

# DataFrame
In [303]: unsorted_df.sort_index()
Out[303]:
      three       two       one
a       NaN -1.152244  0.562973
b -0.098217  0.009797 -1.299504
c  1.273388 -0.167123  0.640382
d -0.252916 -0.109597       NaN

In [304]: unsorted_df.sort_index(ascending=False)
Out[304]:
      three       two       one
d -0.252916 -0.109597       NaN
c  1.273388 -0.167123  0.640382
b -0.098217  0.009797 -1.299504
a       NaN -1.152244  0.562973

In [305]: unsorted_df.sort_index(axis=1)
Out[305]:
        one     three       two
a  0.562973       NaN -1.152244
d       NaN -0.252916 -0.109597
c  0.640382  1.273388 -0.167123
b -1.299504 -0.098217  0.009797

# Series
In [306]: unsorted_df["three"].sort_index()
Out[306]:
a         NaN
b   -0.098217
c    1.273388
d   -0.252916
Name: three, dtype: float64
```

New in version 1.1.0.

Sorting by index also supports a `key` parameter that takes a callable function to apply to the index being sorted. For `MultiIndex` objects, the key is applied per-level to the levels specified by `level`.

```
In [307]: s1 = pd.DataFrame({"a": ["B", "a", "C"], "b": [1, 2, 3], "c": [2, 3, 4]}).
↪set_index(
   .....:     list("ab")
   .....: )
   .....:
```

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```
In [308]: s1
Out[308]:
     c
a b
B 1  2
a 2  3
C 3  4
```

```
In [309]: s1.sort_index(level="a")
Out[309]:
     c
a b
B 1  2
C 3  4
a 2  3

In [310]: s1.sort_index(level="a", key=lambda idx: idx.str.lower())
Out[310]:
     c
a b
a 2  3
B 1  2
C 3  4
```

For information on key sorting by value, see *value sorting*.

By values

The *Series.sort_values()* method is used to sort a `Series` by its values. The *DataFrame.sort_values()* method is used to sort a `DataFrame` by its column or row values. The optional `by` parameter to *DataFrame.sort_values()* may used to specify one or more columns to use to determine the sorted order.

```
In [311]: df1 = pd.DataFrame(
   .....:     {"one": [2, 1, 1, 1], "two": [1, 3, 2, 4], "three": [5, 4, 3, 2]}
   .....: )
   .....:

In [312]: df1.sort_values(by="two")
Out[312]:
   one  two  three
0    2    1      5
2    1    2      3
1    1    3      4
3    1    4      2
```

The `by` parameter can take a list of column names, e.g.:

```
In [313]: df1[["one", "two", "three"]].sort_values(by=["one", "two"])
Out[313]:
   one  two  three
2    1    2      3
1    1    3      4
3    1    4      2
0    2    1      5
```

These methods have special treatment of NA values via the `na_position` argument:

```
In [314]: s[2] = np.nan

In [315]: s.sort_values()
Out[315]:
0       A
3    Aaba
1       B
4    Baca
6    CABA
8     cat
7     dog
2    <NA>
5    <NA>
dtype: string

In [316]: s.sort_values(na_position="first")
Out[316]:
2    <NA>
5    <NA>
0       A
3    Aaba
1       B
4    Baca
6    CABA
8     cat
7     dog
dtype: string
```

New in version 1.1.0.

Sorting also supports a `key` parameter that takes a callable function to apply to the values being sorted.

```
In [317]: s1 = pd.Series(["B", "a", "C"])
```

```
In [318]: s1.sort_values()
Out[318]:
0    B
2    C
1    a
dtype: object

In [319]: s1.sort_values(key=lambda x: x.str.lower())
Out[319]:
1    a
0    B
2    C
dtype: object
```

`key` will be given the *`Series`* of values and should return a `Series` or array of the same shape with the transformed values. For `DataFrame` objects, the key is applied per column, so the key should still expect a Series and return a Series, e.g.

```
In [320]: df = pd.DataFrame({"a": ["B", "a", "C"], "b": [1, 2, 3]})
```

```
In [321]: df.sort_values(by="a")
Out[321]:
   a  b
```

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```
0  B  1
2  C  3
1  a  2

In [322]: df.sort_values(by="a", key=lambda col: col.str.lower())
Out[322]:
   a  b
1  a  2
0  B  1
2  C  3
```

The name or type of each column can be used to apply different functions to different columns.

By indexes and values

Strings passed as the `by` parameter to *`DataFrame.sort_values()`* may refer to either columns or index level names.

```
# Build MultiIndex
In [323]: idx = pd.MultiIndex.from_tuples(
   .....:     [("a", 1), ("a", 2), ("a", 2), ("b", 2), ("b", 1), ("b", 1)]
   .....: )
   .....:

In [324]: idx.names = ["first", "second"]

# Build DataFrame
In [325]: df_multi = pd.DataFrame({"A": np.arange(6, 0, -1)}, index=idx)

In [326]: df_multi
Out[326]:
              A
first second
a     1       6
      2       5
      2       4
b     2       3
      1       2
      1       1
```

Sort by 'second' (index) and 'A' (column)

```
In [327]: df_multi.sort_values(by=["second", "A"])
Out[327]:
              A
first second
b     1       1
      1       2
a     1       6
b     2       3
a     2       4
      2       5
```

Note: If a string matches both a column name and an index level name then a warning is issued and the column takes

precedence. This will result in an ambiguity error in a future version.

searchsorted

Series has the *searchsorted()* method, which works similarly to numpy.ndarray.searchsorted().

```
In [328]: ser = pd.Series([1, 2, 3])

In [329]: ser.searchsorted([0, 3])
Out[329]: array([0, 2])

In [330]: ser.searchsorted([0, 4])
Out[330]: array([0, 3])

In [331]: ser.searchsorted([1, 3], side="right")
Out[331]: array([1, 3])

In [332]: ser.searchsorted([1, 3], side="left")
Out[332]: array([0, 2])

In [333]: ser = pd.Series([3, 1, 2])

In [334]: ser.searchsorted([0, 3], sorter=np.argsort(ser))
Out[334]: array([0, 2])
```

smallest / largest values

Series has the *nsmallest()* and *nlargest()* methods which return the smallest or largest n values. For a large Series this can be much faster than sorting the entire Series and calling head(n) on the result.

```
In [335]: s = pd.Series(np.random.permutation(10))

In [336]: s
Out[336]:
0    2
1    0
2    3
3    7
4    1
5    5
6    9
7    6
8    8
9    4
dtype: int64

In [337]: s.sort_values()
Out[337]:
1    0
4    1
0    2
2    3
9    4
5    5
```

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```
7    6
3    7
8    8
6    9
dtype: int64

In [338]: s.nsmallest(3)
Out[338]:
1    0
4    1
0    2
dtype: int64

In [339]: s.nlargest(3)
Out[339]:
6    9
8    8
3    7
dtype: int64
```

`DataFrame` also has the `nlargest` and `nsmallest` methods.

```
In [340]: df = pd.DataFrame(
   .....:     {
   .....:         "a": [-2, -1, 1, 10, 8, 11, -1],
   .....:         "b": list("abdceff"),
   .....:         "c": [1.0, 2.0, 4.0, 3.2, np.nan, 3.0, 4.0],
   .....:     }
   .....: )
   .....:

In [341]: df.nlargest(3, "a")
Out[341]:
    a  b    c
5  11  f  3.0
3  10  c  3.2
4   8  e  NaN

In [342]: df.nlargest(5, ["a", "c"])
Out[342]:
    a  b    c
5  11  f  3.0
3  10  c  3.2
4   8  e  NaN
2   1  d  4.0
6  -1  f  4.0

In [343]: df.nsmallest(3, "a")
Out[343]:
   a  b    c
0 -2  a  1.0
1 -1  b  2.0
6 -1  f  4.0

In [344]: df.nsmallest(5, ["a", "c"])
Out[344]:
   a  b    c
```

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```
0 -2  a  1.0
1 -1  b  2.0
6 -1  f  4.0
2  1  d  4.0
4  8  e  NaN
```

Sorting by a MultiIndex column

You must be explicit about sorting when the column is a MultiIndex, and fully specify all levels to `by`.

```
In [345]: df1.columns = pd.MultiIndex.from_tuples(
   .....:     [("a", "one"), ("a", "two"), ("b", "three")]
   .....: )
   .....:

In [346]: df1.sort_values(by=("a", "two"))
Out[346]:
    a          b
  one two three
0   2   1     5
2   1   2     3
1   1   3     4
3   1   4     2
```

2.3.12 Copying

The *copy()* method on pandas objects copies the underlying data (though not the axis indexes, since they are immutable) and returns a new object. Note that **it is seldom necessary to copy objects**. For example, there are only a handful of ways to alter a DataFrame *in-place*:

- Inserting, deleting, or modifying a column.
- Assigning to the `index` or `columns` attributes.
- For homogeneous data, directly modifying the values via the `values` attribute or advanced indexing.

To be clear, no pandas method has the side effect of modifying your data; almost every method returns a new object, leaving the original object untouched. If the data is modified, it is because you did so explicitly.

2.3.13 dtypes

For the most part, pandas uses NumPy arrays and dtypes for Series or individual columns of a DataFrame. NumPy provides support for `float`, `int`, `bool`, `timedelta64[ns]` and `datetime64[ns]` (note that NumPy does not support timezone-aware datetimes).

pandas and third-party libraries *extend* NumPy's type system in a few places. This section describes the extensions pandas has made internally. See *Extension types* for how to write your own extension that works with pandas. See ecosystem.extensions for a list of third-party libraries that have implemented an extension.

The following table lists all of pandas extension types. For methods requiring `dtype` arguments, strings can be specified as indicated. See the respective documentation sections for more on each type.

Kind of Data	Data Type	Scalar	Array	String Aliases	Documentation
tz-aware datetime	*DatetimeTZDtype*	*Timestamp*	*arrays.DatetimeArray*	'datetime64[ns, <tz>]'	*Time zone handling*
Categorical	*CategoricalDtype*	(none)	*Categorical*	'category'	*Categorical data*
period (time spans)	*PeriodDtype*	*Period*	*arrays.PeriodArray*	'period[<freq>]','Period[<freq>]'	*Time span representation*
sparse	*SparseDtype*	(none)	*arrays.SparseArray*	'Sparse','Sparse[int]','Sparse[float]'	*Sparse data structures*
intervals	*IntervalDtype*	*Interval*	*arrays.IntervalArray*	'interval', 'Interval', 'Interval[<numpy_dtype>]', 'Interval[datetime64[ns, <tz>]]', 'Interval[timedelta64[<freq>]]'	*IntervalIndex*
nullable integer	*Int64Dtype*, ...	(none)	*arrays.IntegerArray*	'Int8','Int16','Int32','Int64','UInt8','UInt16','UInt32','UInt64'	*Nullable integer data type*
Strings	*StringDtype*	*str*	*arrays.StringArray*	'string'	*Working with text data*
Boolean (with NA)	*BooleanDtype*	*bool*	*arrays.BooleanArray*	'boolean'	*Boolean data with missing values*

pandas has two ways to store strings.

1. `object` dtype, which can hold any Python object, including strings.
2. *StringDtype*, which is dedicated to strings.

Generally, we recommend using *StringDtype*. See *Text data types* for more.

Finally, arbitrary objects may be stored using the `object` dtype, but should be avoided to the extent possible (for performance and interoperability with other libraries and methods. See *object conversion*).

A convenient *dtypes* attribute for DataFrame returns a Series with the data type of each column.

```
In [347]: dft = pd.DataFrame(
   .....:     {
   .....:         "A": np.random.rand(3),
   .....:         "B": 1,
   .....:         "C": "foo",
   .....:         "D": pd.Timestamp("20010102"),
   .....:         "E": pd.Series([1.0] * 3).astype("float32"),
   .....:         "F": False,
   .....:         "G": pd.Series([1] * 3, dtype="int8"),
   .....:     }
   .....: )
   .....:
```

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```
In [348]: dft
Out[348]:
          A  B    C          D    E      F  G
0  0.035962  1  foo 2001-01-02  1.0  False  1
1  0.701379  1  foo 2001-01-02  1.0  False  1
2  0.281885  1  foo 2001-01-02  1.0  False  1

In [349]: dft.dtypes
Out[349]:
A           float64
B             int64
C            object
D    datetime64[ns]
E           float32
F              bool
G              int8
dtype: object
```

On a `Series` object, use the *`dtype`* attribute.

```
In [350]: dft["A"].dtype
Out[350]: dtype('float64')
```

If a pandas object contains data with multiple dtypes *in a single column*, the dtype of the column will be chosen to accommodate all of the data types (`object` is the most general).

```
# these ints are coerced to floats
In [351]: pd.Series([1, 2, 3, 4, 5, 6.0])
Out[351]:
0    1.0
1    2.0
2    3.0
3    4.0
4    5.0
5    6.0
dtype: float64

# string data forces an ``object`` dtype
In [352]: pd.Series([1, 2, 3, 6.0, "foo"])
Out[352]:
0      1
1      2
2      3
3    6.0
4    foo
dtype: object
```

The number of columns of each type in a `DataFrame` can be found by calling `DataFrame.dtypes.value_counts()`.

```
In [353]: dft.dtypes.value_counts()
Out[353]:
float32           1
datetime64[ns]    1
float64           1
```

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```
bool              1
int8              1
object            1
int64             1
dtype: int64
```

Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`), then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```
In [354]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=["A"], dtype="float32")

In [355]: df1
Out[355]:
          A
0  0.224364
1  1.890546
2  0.182879
3  0.787847
4 -0.188449
5  0.667715
6 -0.011736
7 -0.399073

In [356]: df1.dtypes
Out[356]:
A    float32
dtype: object

In [357]: df2 = pd.DataFrame(
   .....:     {
   .....:         "A": pd.Series(np.random.randn(8), dtype="float16"),
   .....:         "B": pd.Series(np.random.randn(8)),
   .....:         "C": pd.Series(np.array(np.random.randn(8), dtype="uint8")),
   .....:     }
   .....: )
   .....:

In [358]: df2
Out[358]:
          A         B    C
0  0.823242  0.256090    0
1  1.607422  1.426469    0
2 -0.333740 -0.416203  255
3 -0.063477  1.139976    0
4 -1.014648 -1.193477    0
5  0.678711  0.096706    0
6 -0.040863 -1.956850    1
7 -0.357422 -0.714337    0

In [359]: df2.dtypes
Out[359]:
A    float16
B    float64
C      uint8
dtype: object
```

defaults

By default integer types are `int64` and float types are `float64`, *regardless* of platform (32-bit or 64-bit). The following will all result in `int64` dtypes.

```
In [360]: pd.DataFrame([1, 2], columns=["a"]).dtypes
Out[360]:
a    int64
dtype: object

In [361]: pd.DataFrame({"a": [1, 2]}).dtypes
Out[361]:
a    int64
dtype: object

In [362]: pd.DataFrame({"a": 1}, index=list(range(2))).dtypes
Out[362]:
a    int64
dtype: object
```

Note that Numpy will choose *platform-dependent* types when creating arrays. The following **WILL** result in `int32` on 32-bit platform.

```
In [363]: frame = pd.DataFrame(np.array([1, 2]))
```

upcasting

Types can potentially be *upcasted* when combined with other types, meaning they are promoted from the current type (e.g. `int` to `float`).

```
In [364]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [365]: df3
Out[365]:
          A         B      C
0  1.047606  0.256090    0.0
1  3.497968  1.426469    0.0
2 -0.150862 -0.416203  255.0
3  0.724370  1.139976    0.0
4 -1.203098 -1.193477    0.0
5  1.346426  0.096706    0.0
6 -0.052599 -1.956850    1.0
7 -0.756495 -0.714337    0.0

In [366]: df3.dtypes
Out[366]:
A    float32
B    float64
C    float64
dtype: object
```

`DataFrame.to_numpy()` will return the *lower-common-denominator* of the dtypes, meaning the dtype that can accommodate **ALL** of the types in the resulting homogeneous dtyped NumPy array. This can force some *upcasting*.

```
In [367]: df3.to_numpy().dtype
Out[367]: dtype('float64')
```

astype

You can use the *astype()* method to explicitly convert dtypes from one to another. These will by default return a copy, even if the dtype was unchanged (pass `copy=False` to change this behavior). In addition, they will raise an exception if the astype operation is invalid.

Upcasting is always according to the **NumPy** rules. If two different dtypes are involved in an operation, then the more *general* one will be used as the result of the operation.

```
In [368]: df3
Out[368]:
          A         B      C
0  1.047606  0.256090    0.0
1  3.497968  1.426469    0.0
2 -0.150862 -0.416203  255.0
3  0.724370  1.139976    0.0
4 -1.203098 -1.193477    0.0
5  1.346426  0.096706    0.0
6 -0.052599 -1.956850    1.0
7 -0.756495 -0.714337    0.0

In [369]: df3.dtypes
Out[369]:
A    float32
B    float64
C    float64
dtype: object

# conversion of dtypes
In [370]: df3.astype("float32").dtypes
Out[370]:
A    float32
B    float32
C    float32
dtype: object
```

Convert a subset of columns to a specified type using *astype()*.

```
In [371]: dft = pd.DataFrame({"a": [1, 2, 3], "b": [4, 5, 6], "c": [7, 8, 9]})

In [372]: dft[["a", "b"]] = dft[["a", "b"]].astype(np.uint8)

In [373]: dft
Out[373]:
   a  b  c
0  1  4  7
1  2  5  8
2  3  6  9

In [374]: dft.dtypes
Out[374]:
a    uint8
b    uint8
c    int64
dtype: object
```

Convert certain columns to a specific dtype by passing a dict to *astype()*.

```
In [375]: dft1 = pd.DataFrame({"a": [1, 0, 1], "b": [4, 5, 6], "c": [7, 8, 9]})

In [376]: dft1 = dft1.astype({"a": np.bool_, "c": np.float64})

In [377]: dft1
Out[377]:
       a  b    c
0   True  4  7.0
1  False  5  8.0
2   True  6  9.0

In [378]: dft1.dtypes
Out[378]:
a       bool
b      int64
c    float64
dtype: object
```

Note: When trying to convert a subset of columns to a specified type using *astype()* and *loc()*, upcasting occurs.

loc() tries to fit in what we are assigning to the current dtypes, while `[]` will overwrite them taking the dtype from the right hand side. Therefore the following piece of code produces the unintended result.

```
In [379]: dft = pd.DataFrame({"a": [1, 2, 3], "b": [4, 5, 6], "c": [7, 8, 9]})

In [380]: dft.loc[:, ["a", "b"]].astype(np.uint8).dtypes
Out[380]:
a    uint8
b    uint8
dtype: object

In [381]: dft.loc[:, ["a", "b"]] = dft.loc[:, ["a", "b"]].astype(np.uint8)

In [382]: dft.dtypes
Out[382]:
a    int64
b    int64
c    int64
dtype: object
```

object conversion

pandas offers various functions to try to force conversion of types from the `object` dtype to other types. In cases where the data is already of the correct type, but stored in an `object` array, the *DataFrame.infer_objects()* and *Series.infer_objects()* methods can be used to soft convert to the correct type.

```
In [383]: import datetime

In [384]: df = pd.DataFrame(
   .....:     [
   .....:         [1, 2],
   .....:         ["a", "b"],
   .....:         [datetime.datetime(2016, 3, 2), datetime.datetime(2016, 3,␣
↪2)],
```

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```
   .....:     ]
   .....: )
   .....:

In [385]: df = df.T

In [386]: df
Out[386]:
   0  1          2
0  1  a 2016-03-02
1  2  b 2016-03-02

In [387]: df.dtypes
Out[387]:
0            object
1            object
2    datetime64[ns]
dtype: object
```

Because the data was transposed the original inference stored all columns as object, which `infer_objects` will correct.

```
In [388]: df.infer_objects().dtypes
Out[388]:
0             int64
1            object
2    datetime64[ns]
dtype: object
```

The following functions are available for one dimensional object arrays or scalars to perform hard conversion of objects to a specified type:

- *to_numeric()* (conversion to numeric dtypes)

```
In [389]: m = ["1.1", 2, 3]

In [390]: pd.to_numeric(m)
Out[390]: array([1.1, 2. , 3. ])
```

- *to_datetime()* (conversion to datetime objects)

```
In [391]: import datetime

In [392]: m = ["2016-07-09", datetime.datetime(2016, 3, 2)]

In [393]: pd.to_datetime(m)
Out[393]: DatetimeIndex(['2016-07-09', '2016-03-02'], dtype='datetime64[ns]',␣
↪freq=None)
```

- *to_timedelta()* (conversion to timedelta objects)

```
In [394]: m = ["5us", pd.Timedelta("1day")]

In [395]: pd.to_timedelta(m)
Out[395]: TimedeltaIndex(['0 days 00:00:00.000005', '1 days 00:00:00'], dtype=
↪'timedelta64[ns]', freq=None)
```

To force a conversion, we can pass in an `errors` argument, which specifies how pandas should deal with elements that cannot be converted to desired dtype or object. By default, `errors='raise'`, meaning that any errors encountered will be raised during the conversion process. However, if `errors='coerce'`, these errors will be ignored and pandas will convert problematic elements to `pd.NaT` (for datetime and timedelta) or `np.nan` (for numeric). This might be useful if you are reading in data which is mostly of the desired dtype (e.g. numeric, datetime), but occasionally has non-conforming elements intermixed that you want to represent as missing:

```
In [396]: import datetime

In [397]: m = ["apple", datetime.datetime(2016, 3, 2)]

In [398]: pd.to_datetime(m, errors="coerce")
Out[398]: DatetimeIndex(['NaT', '2016-03-02'], dtype='datetime64[ns]', freq=None)

In [399]: m = ["apple", 2, 3]

In [400]: pd.to_numeric(m, errors="coerce")
Out[400]: array([nan,  2.,  3.])

In [401]: m = ["apple", pd.Timedelta("1day")]

In [402]: pd.to_timedelta(m, errors="coerce")
Out[402]: TimedeltaIndex([NaT, '1 days'], dtype='timedelta64[ns]', freq=None)
```

The `errors` parameter has a third option of `errors='ignore'`, which will simply return the passed in data if it encounters any errors with the conversion to a desired data type:

```
In [403]: import datetime

In [404]: m = ["apple", datetime.datetime(2016, 3, 2)]

In [405]: pd.to_datetime(m, errors="ignore")
Out[405]: Index(['apple', 2016-03-02 00:00:00], dtype='object')

In [406]: m = ["apple", 2, 3]

In [407]: pd.to_numeric(m, errors="ignore")
Out[407]: array(['apple', 2, 3], dtype=object)

In [408]: m = ["apple", pd.Timedelta("1day")]

In [409]: pd.to_timedelta(m, errors="ignore")
Out[409]: array(['apple', Timedelta('1 days 00:00:00')], dtype=object)
```

In addition to object conversion, *`to_numeric()`* provides another argument `downcast`, which gives the option of downcasting the newly (or already) numeric data to a smaller dtype, which can conserve memory:

```
In [410]: m = ["1", 2, 3]

In [411]: pd.to_numeric(m, downcast="integer")  # smallest signed int dtype
Out[411]: array([1, 2, 3], dtype=int8)

In [412]: pd.to_numeric(m, downcast="signed")  # same as 'integer'
Out[412]: array([1, 2, 3], dtype=int8)

In [413]: pd.to_numeric(m, downcast="unsigned")  # smallest unsigned int dtype
Out[413]: array([1, 2, 3], dtype=uint8)
```

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```
In [414]: pd.to_numeric(m, downcast="float")  # smallest float dtype
Out[414]: array([1., 2., 3.], dtype=float32)
```

As these methods apply only to one-dimensional arrays, lists or scalars; they cannot be used directly on multi-dimensional objects such as DataFrames. However, with *apply()*, we can "apply" the function over each column efficiently:

```
In [415]: import datetime

In [416]: df = pd.DataFrame([["2016-07-09", datetime.datetime(2016, 3, 2)]] * 2,␣
↪dtype="O")

In [417]: df
Out[417]:
            0                    1
0  2016-07-09  2016-03-02 00:00:00
1  2016-07-09  2016-03-02 00:00:00

In [418]: df.apply(pd.to_datetime)
Out[418]:
           0          1
0 2016-07-09 2016-03-02
1 2016-07-09 2016-03-02

In [419]: df = pd.DataFrame([["1.1", 2, 3]] * 2, dtype="O")

In [420]: df
Out[420]:
     0  1  2
0  1.1  2  3
1  1.1  2  3

In [421]: df.apply(pd.to_numeric)
Out[421]:
     0  1  2
0  1.1  2  3
1  1.1  2  3

In [422]: df = pd.DataFrame([["5us", pd.Timedelta("1day")]] * 2, dtype="O")

In [423]: df
Out[423]:
     0                1
0  5us  1 days 00:00:00
1  5us  1 days 00:00:00

In [424]: df.apply(pd.to_timedelta)
Out[424]:
                       0      1
0 0 days 00:00:00.000005 1 days
1 0 days 00:00:00.000005 1 days
```

gotchas

Performing selection operations on `integer` type data can easily upcast the data to `floating`. The dtype of the input data will be preserved in cases where `nans` are not introduced. See also *Support for integer NA*.

```
In [425]: dfi = df3.astype("int32")

In [426]: dfi["E"] = 1

In [427]: dfi
Out[427]:
   A  B    C  E
0  1  0    0  1
1  3  1    0  1
2  0  0  255  1
3  0  1    0  1
4 -1 -1    0  1
5  1  0    0  1
6  0 -1    1  1
7  0  0    0  1

In [428]: dfi.dtypes
Out[428]:
A    int32
B    int32
C    int32
E    int64
dtype: object

In [429]: casted = dfi[dfi > 0]

In [430]: casted
Out[430]:
     A    B      C  E
0  1.0  NaN    NaN  1
1  3.0  1.0    NaN  1
2  NaN  NaN  255.0  1
3  NaN  1.0    NaN  1
4  NaN  NaN    NaN  1
5  1.0  NaN    NaN  1
6  NaN  NaN    1.0  1
7  NaN  NaN    NaN  1

In [431]: casted.dtypes
Out[431]:
A    float64
B    float64
C    float64
E      int64
dtype: object
```

While float dtypes are unchanged.

```
In [432]: dfa = df3.copy()

In [433]: dfa["A"] = dfa["A"].astype("float32")

In [434]: dfa.dtypes
```

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```
Out[434]:
A    float32
B    float64
C    float64
dtype: object

In [435]: casted = dfa[df2 > 0]

In [436]: casted
Out[436]:
          A         B      C
0  1.047606  0.256090    NaN
1  3.497968  1.426469    NaN
2       NaN       NaN  255.0
3       NaN  1.139976    NaN
4       NaN       NaN    NaN
5  1.346426  0.096706    NaN
6       NaN       NaN    1.0
7       NaN       NaN    NaN

In [437]: casted.dtypes
Out[437]:
A    float32
B    float64
C    float64
dtype: object
```

2.3.14 Selecting columns based on `dtype`

The *`select_dtypes()`* method implements subsetting of columns based on their `dtype`.

First, let's create a *`DataFrame`* with a slew of different dtypes:

```
In [438]: df = pd.DataFrame(
   .....:     {
   .....:         "string": list("abc"),
   .....:         "int64": list(range(1, 4)),
   .....:         "uint8": np.arange(3, 6).astype("u1"),
   .....:         "float64": np.arange(4.0, 7.0),
   .....:         "bool1": [True, False, True],
   .....:         "bool2": [False, True, False],
   .....:         "dates": pd.date_range("now", periods=3),
   .....:         "category": pd.Series(list("ABC")).astype("category"),
   .....:     }
   .....: )
   .....:

In [439]: df["tdeltas"] = df.dates.diff()

In [440]: df["uint64"] = np.arange(3, 6).astype("u8")

In [441]: df["other_dates"] = pd.date_range("20130101", periods=3)

In [442]: df["tz_aware_dates"] = pd.date_range("20130101", periods=3, tz="US/Eastern")
```

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```
In [443]: df
Out[443]:
  string  int64  uint8  float64  bool1  ...  category tdeltas uint64 other_dates
↪       tz_aware_dates
0      a      1      3      4.0   True  ...         A     NaT      3  2013-01-01 2013-
↪01-01 00:00:00-05:00
1      b      2      4      5.0  False  ...         B  1 days      4  2013-01-02 2013-
↪01-02 00:00:00-05:00
2      c      3      5      6.0   True  ...         C  1 days      5  2013-01-03 2013-
↪01-03 00:00:00-05:00

[3 rows x 12 columns]
```

And the dtypes:

```
In [444]: df.dtypes
Out[444]:
string                                object
int64                                  int64
uint8                                  uint8
float64                              float64
bool1                                   bool
bool2                                   bool
dates                         datetime64[ns]
category                            category
tdeltas                      timedelta64[ns]
uint64                                uint64
other_dates                   datetime64[ns]
tz_aware_dates    datetime64[ns, US/Eastern]
dtype: object
```

select_dtypes() has two parameters `include` and `exclude` that allow you to say "give me the columns *with* these dtypes" (`include`) and/or "give the columns *without* these dtypes" (`exclude`).

For example, to select `bool` columns:

```
In [445]: df.select_dtypes(include=[bool])
Out[445]:
   bool1  bool2
0   True  False
1  False   True
2   True  False
```

You can also pass the name of a dtype in the NumPy dtype hierarchy:

```
In [446]: df.select_dtypes(include=["bool"])
Out[446]:
   bool1  bool2
0   True  False
1  False   True
2   True  False
```

select_dtypes() also works with generic dtypes as well.

For example, to select all numeric and boolean columns while excluding unsigned integers:

```
In [447]: df.select_dtypes(include=["number", "bool"], exclude=["unsignedinteger"])
Out[447]:
   int64  float64  bool1  bool2 tdeltas
0      1      4.0   True  False     NaT
1      2      5.0  False   True  1 days
2      3      6.0   True  False  1 days
```

To select string columns you must use the `object` dtype:

```
In [448]: df.select_dtypes(include=["object"])
Out[448]:
  string
0      a
1      b
2      c
```

To see all the child dtypes of a generic `dtype` like `numpy.number` you can define a function that returns a tree of child dtypes:

```
In [449]: def subdtypes(dtype):
   .....:     subs = dtype.__subclasses__()
   .....:     if not subs:
   .....:         return dtype
   .....:     return [dtype, [subdtypes(dt) for dt in subs]]
   .....:
```

All NumPy dtypes are subclasses of `numpy.generic`:

```
In [450]: subdtypes(np.generic)
Out[450]:
[numpy.generic,
 [[numpy.number,
   [[numpy.integer,
     [[numpy.signedinteger,
       [numpy.int8,
        numpy.int16,
        numpy.int32,
        numpy.int64,
        numpy.longlong,
        numpy.timedelta64]],
      [numpy.unsignedinteger,
       [numpy.uint8,
        numpy.uint16,
        numpy.uint32,
        numpy.uint64,
        numpy.ulonglong]]]],
    [numpy.inexact,
     [[numpy.floating,
       [numpy.float16, numpy.float32, numpy.float64, numpy.float128]],
      [numpy.complexfloating,
       [numpy.complex64, numpy.complex128, numpy.complex256]]]]],
  [numpy.flexible,
   [[numpy.character, [numpy.bytes_, numpy.str_]],
    [numpy.void, [numpy.record]]]],
  numpy.bool_,
  numpy.datetime64,
  numpy.object_]]
```

Note: pandas also defines the types `category`, and `datetime64[ns, tz]`, which are not integrated into the normal NumPy hierarchy and won't show up with the above function.

2.4 IO tools (text, CSV, HDF5, . . .)

The pandas I/O API is a set of top level `reader` functions accessed like *pandas.read_csv()* that generally return a pandas object. The corresponding `writer` functions are object methods that are accessed like *DataFrame.to_csv()*. Below is a table containing available `readers` and `writers`.

Format Type	Data Description	Reader	Writer
text	CSV	*read_csv*	*to_csv*
text	Fixed-Width Text File	*read_fwf*	
text	JSON	*read_json*	*to_json*
text	HTML	*read_html*	*to_html*
text	Local clipboard	*read_clipboard*	*to_clipboard*
binary	MS Excel	*read_excel*	*to_excel*
binary	OpenDocument	*read_excel*	
binary	HDF5 Format	*read_hdf*	*to_hdf*
binary	Feather Format	*read_feather*	*to_feather*
binary	Parquet Format	*read_parquet*	*to_parquet*
binary	ORC Format	*read_orc*	
binary	Msgpack	*read_msgpack*	*to_msgpack*
binary	Stata	*read_stata*	*to_stata*
binary	SAS	*read_sas*	
binary	SPSS	*read_spss*	
binary	Python Pickle Format	*read_pickle*	*to_pickle*
SQL	SQL	*read_sql*	*to_sql*
SQL	Google BigQuery	*read_gbq*	*to_gbq*

Here is an informal performance comparison for some of these IO methods.

Note: For examples that use the `StringIO` class, make sure you import it with `from io import StringIO` for Python 3.

2.4.1 CSV & text files

The workhorse function for reading text files (a.k.a. flat files) is *read_csv()*. See the *cookbook* for some advanced strategies.

Parsing options

read_csv() accepts the following common arguments:

Basic

filepath_or_buffer [various] Either a path to a file (a str, pathlib.Path, or py._path.local.LocalPath), URL (including http, ftp, and S3 locations), or any object with a read() method (such as an open file or StringIO).

sep [str, defaults to ',' for *read_csv()*, \t for *read_table()*] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python's builtin sniffer tool, csv.Sniffer. In addition, separators longer than 1 character and different from '\s+' will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: '\\r\\t'.

delimiter [str, default None] Alternative argument name for sep.

delim_whitespace [boolean, default False] Specifies whether or not whitespace (e.g. ' ' or '\t') will be used as the delimiter. Equivalent to setting sep='\s+'. If this option is set to True, nothing should be passed in for the delimiter parameter.

Column and index locations and names

header [int or list of ints, default 'infer'] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to header=0 and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to header=None. Explicitly pass header=0 to be able to replace existing names.

The header can be a list of ints that specify row locations for a MultiIndex on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if skip_blank_lines=True, so header=0 denotes the first line of data rather than the first line of the file.

names [array-like, default None] List of column names to use. If file contains no header row, then you should explicitly pass header=None. Duplicates in this list are not allowed.

index_col [int, str, sequence of int / str, or False, default None] Column(s) to use as the row labels of the DataFrame, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.

Note: index_col=False can be used to force pandas to *not* use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

The default value of None instructs pandas to guess. If the number of fields in the column header row is equal to the number of fields in the body of the data file, then a default index is used. If it is one larger, then the first field is used as an index.

usecols [list-like or callable, default None] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in names or inferred from the document header row(s). For example, a valid list-like usecols parameter would be [0, 1, 2] or ['foo', 'bar', 'baz'].

Element order is ignored, so usecols=[0, 1] is the same as [1, 0]. To instantiate a DataFrame from data with element order preserved use pd.read_csv(data, usecols=['foo',

`'bar'])[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True:

```
In [1]: import pandas as pd

In [2]: from io import StringIO

In [3]: data = "col1,col2,col3\na,b,1\na,b,2\nc,d,3"

In [4]: pd.read_csv(StringIO(data))
Out[4]:
  col1 col2  col3
0    a    b     1
1    a    b     2
2    c    d     3

In [5]: pd.read_csv(StringIO(data), usecols=lambda x: x.upper() in ["COL1", "COL3
↪"])
Out[5]:
  col1  col3
0    a     1
1    a     2
2    c     3
```

Using this parameter results in much faster parsing time and lower memory usage.

squeeze [boolean, default `False`] If the parsed data only contains one column then return a `Series`.

prefix [str, default `None`] Prefix to add to column numbers when no header, e.g. 'X' for X0, X1, ...

mangle_dupe_cols [boolean, default `True`] Duplicate columns will be specified as 'X', 'X.1'...'X.N', rather than 'X'...'X'. Passing in `False` will cause data to be overwritten if there are duplicate names in the columns.

General parsing configuration

dtype [Type name or dict of column -> type, default `None`] Data type for data or columns. E.g. `{'a': np.float64, 'b': np.int32}` (unsupported with `engine='python'`). Use `str` or `object` together with suitable `na_values` settings to preserve and not interpret dtype.

engine [{`'c'`, `'python'`}] Parser engine to use. The C engine is faster while the Python engine is currently more feature-complete.

converters [dict, default `None`] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

true_values [list, default `None`] Values to consider as `True`.

false_values [list, default `None`] Values to consider as `False`.

skipinitialspace [boolean, default `False`] Skip spaces after delimiter.

skiprows [list-like or integer, default `None`] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise:

```
In [6]: data = "col1,col2,col3\na,b,1\na,b,2\nc,d,3"

In [7]: pd.read_csv(StringIO(data))
Out[7]:
  col1 col2  col3
0    a    b     1
1    a    b     2
2    c    d     3

In [8]: pd.read_csv(StringIO(data), skiprows=lambda x: x % 2 != 0)
Out[8]:
  col1 col2  col3
0    a    b     2
```

skipfooter [int, default `0`] Number of lines at bottom of file to skip (unsupported with engine='c').

nrows [int, default `None`] Number of rows of file to read. Useful for reading pieces of large files.

low_memory [boolean, default `True`] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set `False`, or specify the type with the `dtype` parameter. Note that the entire file is read into a single `DataFrame` regardless, use the `chunksize` or `iterator` parameter to return the data in chunks. (Only valid with C parser)

memory_map [boolean, default False] If a filepath is provided for `filepath_or_buffer`, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

NA and missing data handling

na_values [scalar, str, list-like, or dict, default `None`] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. See *na values const* below for a list of the values interpreted as NaN by default.

keep_default_na [boolean, default `True`] Whether or not to include the default NaN values when parsing the data. Depending on whether `na_values` is passed in, the behavior is as follows:

- If `keep_default_na` is `True`, and `na_values` are specified, `na_values` is appended to the default NaN values used for parsing.
- If `keep_default_na` is `True`, and `na_values` are not specified, only the default NaN values are used for parsing.
- If `keep_default_na` is `False`, and `na_values` are specified, only the NaN values specified `na_values` are used for parsing.
- If `keep_default_na` is `False`, and `na_values` are not specified, no strings will be parsed as NaN.

Note that if `na_filter` is passed in as `False`, the `keep_default_na` and `na_values` parameters will be ignored.

na_filter [boolean, default `True`] Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing `na_filter=False` can improve the performance of reading a large file.

verbose [boolean, default `False`] Indicate number of NA values placed in non-numeric columns.

skip_blank_lines [boolean, default `True`] If `True`, skip over blank lines rather than interpreting as NaN values.

Datetime handling

parse_dates [boolean or list of ints or names or list of lists or dict, default `False`.]

- If `True` -> try parsing the index.
- If `[1, 2, 3]` -> try parsing columns 1, 2, 3 each as a separate date column.
- If `[[1, 3]]` -> combine columns 1 and 3 and parse as a single date column.
- If `{'foo': [1, 3]}` -> parse columns 1, 3 as date and call result 'foo'. A fast-path exists for iso8601-formatted dates.

infer_datetime_format [boolean, default `False`] If `True` and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing.

keep_date_col [boolean, default `False`] If `True` and parse_dates specifies combining multiple columns then keep the original columns.

date_parser [function, default `None`] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. pandas will try to call date_parser in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by parse_dates) as arguments; 2) concatenate (row-wise) the string values from the columns defined by parse_dates into a single array and pass that; and 3) call date_parser once for each row using one or more strings (corresponding to the columns defined by parse_dates) as arguments.

dayfirst [boolean, default `False`] DD/MM format dates, international and European format.

cache_dates [boolean, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

Iteration

iterator [boolean, default `False`] Return `TextFileReader` object for iteration or getting chunks with `get_chunk()`.

chunksize [int, default `None`] Return `TextFileReader` object for iteration. See *iterating and chunking* below.

Quoting, compression, and file format

compression [{`'infer'`, `'gzip'`, `'bz2'`, `'zip'`, `'xz'`, `None`, `dict`}, default `'infer'`] For on-the-fly decompression of on-disk data. If 'infer', then use gzip, bz2, zip, or xz if `filepath_or_buffer` is path-like ending in '.gz', '.bz2', '.zip', or '.xz', respectively, and no decompression otherwise. If using 'zip', the ZIP file must contain only one data file to be read in. Set to `None` for no decompression. Can also be a dict with key `'method'` set to one of {`'zip'`, `'gzip'`, `'bz2'`} and other key-value pairs are forwarded to `zipfile.ZipFile`, `gzip.GzipFile`, or `bz2.BZ2File`. As an example, the following could be passed for faster compression and to create a reproducible gzip archive: `compression={'method': 'gzip', 'compresslevel': 1, 'mtime': 1}`.

Changed in version 0.24.0: 'infer' option added and set to default.

Changed in version 1.1.0: dict option extended to support `gzip` and `bz2`.

Changed in version 1.2.0: Previous versions forwarded dict entries for 'gzip' to `gzip.open`.

thousands [str, default `None`] Thousands separator.

decimal [str, default `'.'`] Character to recognize as decimal point. E.g. use `','` for European data.

float_precision [string, default None] Specifies which converter the C engine should use for floating-point values. The options are `None` for the ordinary converter, `high` for the high-precision converter, and `round_trip` for the round-trip converter.

lineterminator [str (length 1), default `None`] Character to break file into lines. Only valid with C parser.

quotechar [str (length 1)] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting [int or `csv.QUOTE_*` instance, default `0`] Control field quoting behavior per `csv.QUOTE_*` constants. Use one of `QUOTE_MINIMAL` (0), `QUOTE_ALL` (1), `QUOTE_NONNUMERIC` (2) or `QUOTE_NONE` (3).

doublequote [boolean, default `True`] When `quotechar` is specified and `quoting` is not `QUOTE_NONE`, indicate whether or not to interpret two consecutive `quotechar` elements **inside** a field as a single `quotechar` element.

escapechar [str (length 1), default `None`] One-character string used to escape delimiter when quoting is `QUOTE_NONE`.

comment [str, default `None`] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter `header` but not by `skiprows`. For example, if `comment='#'`, parsing '#empty\na,b,c\n1,2,3' with `header=0` will result in 'a,b,c' being treated as the header.

encoding [str, default `None`] Encoding to use for UTF when reading/writing (e.g. `'utf-8'`). List of Python standard encodings.

dialect [str or `csv.Dialect` instance, default `None`] If provided, this parameter will override values (default or not) for the following parameters: `delimiter`, `doublequote`, `escapechar`, `skipinitialspace`, `quotechar`, and `quoting`. If it is necessary to override values, a ParserWarning will be issued. See `csv.Dialect` documentation for more details.

Error handling

error_bad_lines [boolean, default `True`] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no `DataFrame` will be returned. If `False`, then these "bad lines" will dropped from the `DataFrame` that is returned. See *bad lines* below.

warn_bad_lines [boolean, default `True`] If error_bad_lines is `False`, and warn_bad_lines is `True`, a warning for each "bad line" will be output.

Specifying column data types

You can indicate the data type for the whole `DataFrame` or individual columns:

```
In [9]: import numpy as np

In [10]: data = "a,b,c,d\n1,2,3,4\n5,6,7,8\n9,10,11"

In [11]: print(data)
a,b,c,d
1,2,3,4
5,6,7,8
9,10,11

In [12]: df = pd.read_csv(StringIO(data), dtype=object)
```

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```
In [13]: df
Out[13]:
   a   b   c    d
0  1   2   3    4
1  5   6   7    8
2  9  10  11  NaN

In [14]: df["a"][0]
Out[14]: '1'

In [15]: df = pd.read_csv(StringIO(data), dtype={"b": object, "c": np.float64, "d":
↪"Int64"})

In [16]: df.dtypes
Out[16]:
a      int64
b     object
c    float64
d      Int64
dtype: object
```

Fortunately, pandas offers more than one way to ensure that your column(s) contain only one `dtype`. If you're unfamiliar with these concepts, you can see *here* to learn more about dtypes, and *here* to learn more about `object` conversion in pandas.

For instance, you can use the `converters` argument of *`read_csv()`*:

```
In [17]: data = "col_1\n1\n2\n'A'\n4.22"

In [18]: df = pd.read_csv(StringIO(data), converters={"col_1": str})

In [19]: df
Out[19]:
  col_1
0     1
1     2
2   'A'
3  4.22

In [20]: df["col_1"].apply(type).value_counts()
Out[20]:
<class 'str'>    4
Name: col_1, dtype: int64
```

Or you can use the *`to_numeric()`* function to coerce the dtypes after reading in the data,

```
In [21]: df2 = pd.read_csv(StringIO(data))

In [22]: df2["col_1"] = pd.to_numeric(df2["col_1"], errors="coerce")

In [23]: df2
Out[23]:
   col_1
0   1.00
1   2.00
2    NaN
```

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```
3   4.22

In [24]: df2["col_1"].apply(type).value_counts()
Out[24]:
<class 'float'>    4
Name: col_1, dtype: int64
```

which will convert all valid parsing to floats, leaving the invalid parsing as `NaN`.

Ultimately, how you deal with reading in columns containing mixed dtypes depends on your specific needs. In the case above, if you wanted to `NaN` out the data anomalies, then *`to_numeric()`* is probably your best option. However, if you wanted for all the data to be coerced, no matter the type, then using the `converters` argument of *`read_csv()`* would certainly be worth trying.

Note: In some cases, reading in abnormal data with columns containing mixed dtypes will result in an inconsistent dataset. If you rely on pandas to infer the dtypes of your columns, the parsing engine will go and infer the dtypes for different chunks of the data, rather than the whole dataset at once. Consequently, you can end up with column(s) with mixed dtypes. For example,

```
In [25]: col_1 = list(range(500000)) + ["a", "b"] + list(range(500000))

In [26]: df = pd.DataFrame({"col_1": col_1})

In [27]: df.to_csv("foo.csv")

In [28]: mixed_df = pd.read_csv("foo.csv")

In [29]: mixed_df["col_1"].apply(type).value_counts()
Out[29]:
<class 'int'>    737858
<class 'str'>    262144
Name: col_1, dtype: int64

In [30]: mixed_df["col_1"].dtype
Out[30]: dtype('O')
```

will result with `mixed_df` containing an `int` dtype for certain chunks of the column, and `str` for others due to the mixed dtypes from the data that was read in. It is important to note that the overall column will be marked with a `dtype` of `object`, which is used for columns with mixed dtypes.

Specifying categorical dtype

`Categorical` columns can be parsed directly by specifying `dtype='category'` or `dtype=CategoricalDtype(categories, ordered)`.

```
In [31]: data = "col1,col2,col3\na,b,1\na,b,2\nc,d,3"

In [32]: pd.read_csv(StringIO(data))
Out[32]:
  col1 col2  col3
0    a    b     1
1    a    b     2
2    c    d     3
```

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```
In [33]: pd.read_csv(StringIO(data)).dtypes
Out[33]:
col1    object
col2    object
col3     int64
dtype: object

In [34]: pd.read_csv(StringIO(data), dtype="category").dtypes
Out[34]:
col1    category
col2    category
col3    category
dtype: object
```

Individual columns can be parsed as a `Categorical` using a dict specification:

```
In [35]: pd.read_csv(StringIO(data), dtype={"col1": "category"}).dtypes
Out[35]:
col1    category
col2      object
col3       int64
dtype: object
```

Specifying `dtype='category'` will result in an unordered `Categorical` whose `categories` are the unique values observed in the data. For more control on the categories and order, create a `CategoricalDtype` ahead of time, and pass that for that column's `dtype`.

```
In [36]: from pandas.api.types import CategoricalDtype

In [37]: dtype = CategoricalDtype(["d", "c", "b", "a"], ordered=True)

In [38]: pd.read_csv(StringIO(data), dtype={"col1": dtype}).dtypes
Out[38]:
col1    category
col2      object
col3       int64
dtype: object
```

When using `dtype=CategoricalDtype`, "unexpected" values outside of `dtype.categories` are treated as missing values.

```
In [39]: dtype = CategoricalDtype(["a", "b", "d"])  # No 'c'

In [40]: pd.read_csv(StringIO(data), dtype={"col1": dtype}).col1
Out[40]:
0      a
1      a
2    NaN
Name: col1, dtype: category
Categories (3, object): ['a', 'b', 'd']
```

This matches the behavior of `Categorical.set_categories()`.

Note: With `dtype='category'`, the resulting categories will always be parsed as strings (object dtype). If the categories are numeric they can be converted using the *`to_numeric()`* function, or as appropriate, another converter

such as *to_datetime()*.

When `dtype` is a `CategoricalDtype` with homogeneous `categories` (all numeric, all datetimes, etc.), the conversion is done automatically.

```
In [41]: df = pd.read_csv(StringIO(data), dtype="category")

In [42]: df.dtypes
Out[42]:
col1    category
col2    category
col3    category
dtype: object

In [43]: df["col3"]
Out[43]:
0    1
1    2
2    3
Name: col3, dtype: category
Categories (3, object): ['1', '2', '3']

In [44]: df["col3"].cat.categories = pd.to_numeric(df["col3"].cat.categories)

In [45]: df["col3"]
Out[45]:
0    1
1    2
2    3
Name: col3, dtype: category
Categories (3, int64): [1, 2, 3]
```

Naming and using columns

Handling column names

A file may or may not have a header row. pandas assumes the first row should be used as the column names:

```
In [46]: data = "a,b,c\n1,2,3\n4,5,6\n7,8,9"

In [47]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [48]: pd.read_csv(StringIO(data))
Out[48]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

By specifying the `names` argument in conjunction with `header` you can indicate other names to use and whether or not to throw away the header row (if any):

```
In [49]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [50]: pd.read_csv(StringIO(data), names=["foo", "bar", "baz"], header=0)
Out[50]:
   foo  bar  baz
0    1    2    3
1    4    5    6
2    7    8    9

In [51]: pd.read_csv(StringIO(data), names=["foo", "bar", "baz"], header=None)
Out[51]:
  foo bar baz
0   a   b   c
1   1   2   3
2   4   5   6
3   7   8   9
```

If the header is in a row other than the first, pass the row number to `header`. This will skip the preceding rows:

```
In [52]: data = "skip this skip it\na,b,c\n1,2,3\n4,5,6\n7,8,9"

In [53]: pd.read_csv(StringIO(data), header=1)
Out[53]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

Note: Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first non-blank line of the file, if column names are passed explicitly then the behavior is identical to `header=None`.

Duplicate names parsing

If the file or header contains duplicate names, pandas will by default distinguish between them so as to prevent overwriting data:

```
In [54]: data = "a,b,a\n0,1,2\n3,4,5"

In [55]: pd.read_csv(StringIO(data))
Out[55]:
   a  b  a.1
0  0  1    2
1  3  4    5
```

There is no more duplicate data because `mangle_dupe_cols=True` by default, which modifies a series of duplicate columns 'X', ..., 'X' to become 'X', 'X.1', ..., 'X.N'. If `mangle_dupe_cols=False`, duplicate data can arise:

```
In [2]: data = 'a,b,a\n0,1,2\n3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
Out[3]:
   a  b  a
0  2  1  2
1  5  4  5
```

To prevent users from encountering this problem with duplicate data, a `ValueError` exception is raised if `mangle_dupe_cols != True`:

```
In [2]: data = 'a,b,a\n0,1,2\n3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
...
ValueError: Setting mangle_dupe_cols=False is not supported yet
```

Filtering columns (`usecols`)

The `usecols` argument allows you to select any subset of the columns in a file, either using the column names, position numbers or a callable:

```
In [56]: data = "a,b,c,d\n1,2,3,foo\n4,5,6,bar\n7,8,9,baz"

In [57]: pd.read_csv(StringIO(data))
Out[57]:
   a  b  c    d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz

In [58]: pd.read_csv(StringIO(data), usecols=["b", "d"])
Out[58]:
   b    d
0  2  foo
1  5  bar
2  8  baz

In [59]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
Out[59]:
   a  c    d
0  1  3  foo
1  4  6  bar
2  7  9  baz

In [60]: pd.read_csv(StringIO(data), usecols=lambda x: x.upper() in ["A", "C"])
Out[60]:
   a  c
0  1  3
1  4  6
2  7  9
```

The `usecols` argument can also be used to specify which columns not to use in the final result:

```
In [61]: pd.read_csv(StringIO(data), usecols=lambda x: x not in ["a", "c"])
Out[61]:
   b    d
```

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```
0  2  foo
1  5  bar
2  8  baz
```

In this case, the callable is specifying that we exclude the "a" and "c" columns from the output.

Comments and empty lines

Ignoring line comments and empty lines

If the `comment` parameter is specified, then completely commented lines will be ignored. By default, completely blank lines will be ignored as well.

```
In [62]: data = "\na,b,c\n  \n# commented line\n1,2,3\n\n4,5,6"

In [63]: print(data)

a,b,c

# commented line
1,2,3

4,5,6

In [64]: pd.read_csv(StringIO(data), comment="#")
Out[64]:
   a  b  c
0  1  2  3
1  4  5  6
```

If `skip_blank_lines=False`, then `read_csv` will not ignore blank lines:

```
In [65]: data = "a,b,c\n\n1,2,3\n\n\n4,5,6"

In [66]: pd.read_csv(StringIO(data), skip_blank_lines=False)
Out[66]:
     a    b    c
0  NaN  NaN  NaN
1  1.0  2.0  3.0
2  NaN  NaN  NaN
3  NaN  NaN  NaN
4  4.0  5.0  6.0
```

Warning: The presence of ignored lines might create ambiguities involving line numbers; the parameter `header` uses row numbers (ignoring commented/empty lines), while `skiprows` uses line numbers (including commented/empty lines):

```
In [67]: data = "#comment\na,b,c\nA,B,C\n1,2,3"

In [68]: pd.read_csv(StringIO(data), comment="#", header=1)
Out[68]:
   A  B  C
0  1  2  3
```

```
In [69]: data = "A,B,C\n#comment\na,b,c\n1,2,3"

In [70]: pd.read_csv(StringIO(data), comment="#", skiprows=2)
Out[70]:
   a  b  c
0  1  2  3
```

If both `header` and `skiprows` are specified, `header` will be relative to the end of `skiprows`. For example:

```
In [71]: data = (
   ....:     "# empty\n"
   ....:     "# second empty line\n"
   ....:     "# third emptyline\n"
   ....:     "X,Y,Z\n"
   ....:     "1,2,3\n"
   ....:     "A,B,C\n"
   ....:     "1,2.,4.\n"
   ....:     "5.,NaN,10.0\n"
   ....: )
   ....:

In [72]: print(data)
# empty
# second empty line
# third emptyline
X,Y,Z
1,2,3
A,B,C
1,2.,4.
5.,NaN,10.0


In [73]: pd.read_csv(StringIO(data), comment="#", skiprows=4, header=1)
Out[73]:
     A    B     C
0  1.0  2.0   4.0
1  5.0  NaN  10.0
```

Comments

Sometimes comments or meta data may be included in a file:

```
In [74]: print(open("tmp.csv").read())
ID,level,category
Patient1,123000,x # really unpleasant
Patient2,23000,y # wouldn't take his medicine
Patient3,1234018,z # awesome
```

By default, the parser includes the comments in the output:

```
In [75]: df = pd.read_csv("tmp.csv")

In [76]: df
Out[76]:
```

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```
         ID    level                        category
0  Patient1   123000           x # really unpleasant
1  Patient2    23000  y # wouldn't take his medicine
2  Patient3  1234018                     z # awesome
```

We can suppress the comments using the `comment` keyword:

```
In [77]: df = pd.read_csv("tmp.csv", comment="#")

In [78]: df
Out[78]:
         ID    level category
0  Patient1   123000       x
1  Patient2    23000       y
2  Patient3  1234018       z
```

Dealing with Unicode data

The `encoding` argument should be used for encoded unicode data, which will result in byte strings being decoded to unicode in the result:

```
In [79]: from io import BytesIO

In [80]: data = b"word,length\n" b"Tr\xc3\xa4umen,7\n" b"Gr\xc3\xbc\xc3\x9fe,5"

In [81]: data = data.decode("utf8").encode("latin-1")

In [82]: df = pd.read_csv(BytesIO(data), encoding="latin-1")

In [83]: df
Out[83]:
      word  length
0  Träumen       7
1    Grüße       5

In [84]: df["word"][1]
Out[84]: 'Grüße'
```

Some formats which encode all characters as multiple bytes, like UTF-16, won't parse correctly at all without specifying the encoding. Full list of Python standard encodings.

Index columns and trailing delimiters

If a file has one more column of data than the number of column names, the first column will be used as the `DataFrame`'s row names:

```
In [85]: data = "a,b,c\n4,apple,bat,5.7\n8,orange,cow,10"

In [86]: pd.read_csv(StringIO(data))
Out[86]:
        a    b     c
4   apple  bat   5.7
8  orange  cow  10.0
```

```
In [87]: data = "index,a,b,c\n4,apple,bat,5.7\n8,orange,cow,10"

In [88]: pd.read_csv(StringIO(data), index_col=0)
Out[88]:
            a    b     c
index
4       apple  bat   5.7
8      orange  cow  10.0
```

Ordinarily, you can achieve this behavior using the `index_col` option.

There are some exception cases when a file has been prepared with delimiters at the end of each data line, confusing the parser. To explicitly disable the index column inference and discard the last column, pass `index_col=False`:

```
In [89]: data = "a,b,c\n4,apple,bat,\n8,orange,cow,"

In [90]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,

In [91]: pd.read_csv(StringIO(data))
Out[91]:
        a    b   c
4   apple  bat NaN
8  orange  cow NaN

In [92]: pd.read_csv(StringIO(data), index_col=False)
Out[92]:
   a       b    c
0  4   apple  bat
1  8  orange  cow
```

If a subset of data is being parsed using the `usecols` option, the `index_col` specification is based on that subset, not the original data.

```
In [93]: data = "a,b,c\n4,apple,bat,\n8,orange,cow,"

In [94]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,

In [95]: pd.read_csv(StringIO(data), usecols=["b", "c"])
Out[95]:
     b   c
4  bat NaN
8  cow NaN

In [96]: pd.read_csv(StringIO(data), usecols=["b", "c"], index_col=0)
Out[96]:
     b   c
4  bat NaN
8  cow NaN
```

Date Handling

Specifying date columns

To better facilitate working with datetime data, *read_csv()* uses the keyword arguments `parse_dates` and `date_parser` to allow users to specify a variety of columns and date/time formats to turn the input text data into `datetime` objects.

The simplest case is to just pass in `parse_dates=True`:

```
# Use a column as an index, and parse it as dates.
In [97]: df = pd.read_csv("foo.csv", index_col=0, parse_dates=True)

In [98]: df
Out[98]:
            A  B  C
date
2009-01-01  a  1  2
2009-01-02  b  3  4
2009-01-03  c  4  5

# These are Python datetime objects
In [99]: df.index
Out[99]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype=
↪'datetime64[ns]', name='date', freq=None)
```

It is often the case that we may want to store date and time data separately, or store various date fields separately. the `parse_dates` keyword can be used to specify a combination of columns to parse the dates and/or times from.

You can specify a list of column lists to `parse_dates`, the resulting date columns will be prepended to the output (so as to not affect the existing column order) and the new column names will be the concatenation of the component column names:

```
In [100]: print(open("tmp.csv").read())
KORD,19990127, 19:00:00, 18:56:00, 0.8100
KORD,19990127, 20:00:00, 19:56:00, 0.0100
KORD,19990127, 21:00:00, 20:56:00, -0.5900
KORD,19990127, 21:00:00, 21:18:00, -0.9900
KORD,19990127, 22:00:00, 21:56:00, -0.5900
KORD,19990127, 23:00:00, 22:56:00, -0.5900

In [101]: df = pd.read_csv("tmp.csv", header=None, parse_dates=[[1, 2], [1, 3]])

In [102]: df
Out[102]:
                  1_2                 1_3     0     4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

By default the parser removes the component date columns, but you can choose to retain them via the `keep_date_col` keyword:

```
In [103]: df = pd.read_csv(
   .....:     "tmp.csv", header=None, parse_dates=[[1, 2], [1, 3]], keep_date_col=True
   .....: )
   .....:

In [104]: df
Out[104]:
                  1_2                 1_3     0         1           2           3     4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  19990127   19:00:00   18:56:00  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  19990127   20:00:00   19:56:00  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD  19990127   21:00:00   20:56:00 -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD  19990127   21:00:00   21:18:00 -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD  19990127   22:00:00   21:56:00 -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD  19990127   23:00:00   22:56:00 -0.59
```

Note that if you wish to combine multiple columns into a single date column, a nested list must be used. In other words, `parse_dates=[1, 2]` indicates that the second and third columns should each be parsed as separate date columns while `parse_dates=[[1, 2]]` means the two columns should be parsed into a single column.

You can also use a dict to specify custom name columns:

```
In [105]: date_spec = {"nominal": [1, 2], "actual": [1, 3]}

In [106]: df = pd.read_csv("tmp.csv", header=None, parse_dates=date_spec)

In [107]: df
Out[107]:
             nominal              actual     0     4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

It is important to remember that if multiple text columns are to be parsed into a single date column, then a new column is prepended to the data. The `index_col` specification is based off of this new set of columns rather than the original data columns:

```
In [108]: date_spec = {"nominal": [1, 2], "actual": [1, 3]}

In [109]: df = pd.read_csv(
   .....:     "tmp.csv", header=None, parse_dates=date_spec, index_col=0
   .....: )  # index is the nominal column
   .....:

In [110]: df
Out[110]:
                                actual     0     4
nominal
1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

Note: If a column or index contains an unparsable date, the entire column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use *to_datetime()* after `pd.read_csv`.

Note: read_csv has a fast_path for parsing datetime strings in iso8601 format, e.g "2000-01-01T00:01:02+00:00" and similar variations. If you can arrange for your data to store datetimes in this format, load times will be significantly faster, ~20x has been observed.

Date parsing functions

Finally, the parser allows you to specify a custom `date_parser` function to take full advantage of the flexibility of the date parsing API:

```
In [111]: df = pd.read_csv(
   .....:     "tmp.csv", header=None, parse_dates=date_spec, date_parser=pd.to_
↪datetime
   .....: )
   .....:

In [112]: df
Out[112]:
               nominal              actual     0     4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

pandas will try to call the `date_parser` function in three different ways. If an exception is raised, the next one is tried:

1. `date_parser` is first called with one or more arrays as arguments, as defined using `parse_dates` (e.g., `date_parser(['2013', '2013'], ['1', '2'])`).
2. If #1 fails, `date_parser` is called with all the columns concatenated row-wise into a single array (e.g., `date_parser(['2013 1', '2013 2'])`).

Note that performance-wise, you should try these methods of parsing dates in order:

1. Try to infer the format using `infer_datetime_format=True` (see section below).
2. If you know the format, use `pd.to_datetime()`: `date_parser=lambda x: pd.to_datetime(x, format=...)`.
3. If you have a really non-standard format, use a custom `date_parser` function. For optimal performance, this should be vectorized, i.e., it should accept arrays as arguments.

Parsing a CSV with mixed timezones

pandas cannot natively represent a column or index with mixed timezones. If your CSV file contains columns with a mixture of timezones, the default result will be an object-dtype column with strings, even with `parse_dates`.

```
In [113]: content = """\
   .....: a
   .....: 2000-01-01T00:00:00+05:00
   .....: 2000-01-01T00:00:00+06:00"""
   .....:

In [114]: df = pd.read_csv(StringIO(content), parse_dates=["a"])

In [115]: df["a"]
Out[115]:
0    2000-01-01 00:00:00+05:00
1    2000-01-01 00:00:00+06:00
Name: a, dtype: object
```

To parse the mixed-timezone values as a datetime column, pass a partially-applied *to_datetime()* with `utc=True` as the `date_parser`.

```
In [116]: df = pd.read_csv(
   .....:     StringIO(content),
   .....:     parse_dates=["a"],
   .....:     date_parser=lambda col: pd.to_datetime(col, utc=True),
   .....: )
   .....:

In [117]: df["a"]
Out[117]:
0   1999-12-31 19:00:00+00:00
1   1999-12-31 18:00:00+00:00
Name: a, dtype: datetime64[ns, UTC]
```

Inferring datetime format

If you have `parse_dates` enabled for some or all of your columns, and your datetime strings are all formatted the same way, you may get a large speed up by setting `infer_datetime_format=True`. If set, pandas will attempt to guess the format of your datetime strings, and then use a faster means of parsing the strings. 5-10x parsing speeds have been observed. pandas will fallback to the usual parsing if either the format cannot be guessed or the format that was guessed cannot properly parse the entire column of strings. So in general, `infer_datetime_format` should not have any negative consequences if enabled.

Here are some examples of datetime strings that can be guessed (All representing December 30th, 2011 at 00:00:00):

- "20111230"
- "2011/12/30"
- "20111230 00:00:00"
- "12/30/2011 00:00:00"
- "30/Dec/2011 00:00:00"
- "30/December/2011 00:00:00"

Note that `infer_datetime_format` is sensitive to `dayfirst`. With `dayfirst=True`, it will guess "01/12/2011" to be December 1st. With `dayfirst=False` (default) it will guess "01/12/2011" to be January 12th.

```
# Try to infer the format for the index column
In [118]: df = pd.read_csv(
   .....:     "foo.csv",
   .....:     index_col=0,
   .....:     parse_dates=True,
   .....:     infer_datetime_format=True,
   .....: )
   .....:

In [119]: df
Out[119]:
            A  B  C
date
2009-01-01  a  1  2
2009-01-02  b  3  4
2009-01-03  c  4  5
```

International date formats

While US date formats tend to be MM/DD/YYYY, many international formats use DD/MM/YYYY instead. For convenience, a `dayfirst` keyword is provided:

```
In [120]: print(open("tmp.csv").read())
date,value,cat
1/6/2000,5,a
2/6/2000,10,b
3/6/2000,15,c

In [121]: pd.read_csv("tmp.csv", parse_dates=[0])
Out[121]:
        date  value cat
0 2000-01-06      5   a
1 2000-02-06     10   b
2 2000-03-06     15   c

In [122]: pd.read_csv("tmp.csv", dayfirst=True, parse_dates=[0])
Out[122]:
        date  value cat
0 2000-06-01      5   a
1 2000-06-02     10   b
2 2000-06-03     15   c
```

Writing CSVs to binary file objects

New in version 1.2.0.

`df.to_csv(..., mode="wb")` allows writing a CSV to a file object opened binary mode. In most cases, it is not necessary to specify `mode` as Pandas will auto-detect whether the file object is opened in text or binary mode.

```
In [123]: import io

In [124]: data = pd.DataFrame([0, 1, 2])

In [125]: buffer = io.BytesIO()

In [126]: data.to_csv(buffer, encoding="utf-8", compression="gzip")
```

Specifying method for floating-point conversion

The parameter `float_precision` can be specified in order to use a specific floating-point converter during parsing with the C engine. The options are the ordinary converter, the high-precision converter, and the round-trip converter (which is guaranteed to round-trip values after writing to a file). For example:

```
In [127]: val = "0.3066101993807095471566981359501369297504425048828125"

In [128]: data = "a,b,c\n1,2,{0}".format(val)

In [129]: abs(
   .....:     pd.read_csv(
   .....:         StringIO(data),
   .....:         engine="c",
   .....:         float_precision=None,
   .....:     )["c"][0] - float(val)
   .....: )
   .....:
Out[129]: 5.551115123125783e-17

In [130]: abs(
   .....:     pd.read_csv(
   .....:         StringIO(data),
   .....:         engine="c",
   .....:         float_precision="high",
   .....:     )["c"][0] - float(val)
   .....: )
   .....:
Out[130]: 5.551115123125783e-17

In [131]: abs(
   .....:     pd.read_csv(StringIO(data), engine="c", float_precision="round_trip")["c
↪"][0]
   .....:     - float(val)
   .....: )
   .....:
Out[131]: 0.0
```

Thousand separators

For large numbers that have been written with a thousands separator, you can set the `thousands` keyword to a string of length 1 so that integers will be parsed correctly:

By default, numbers with a thousands separator will be parsed as strings:

```
In [132]: print(open("tmp.csv").read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z

In [133]: df = pd.read_csv("tmp.csv", sep="|")

In [134]: df
Out[134]:
         ID      level category
0  Patient1    123,000        x
1  Patient2     23,000        y
2  Patient3  1,234,018        z

In [135]: df.level.dtype
Out[135]: dtype('O')
```

The `thousands` keyword allows integers to be parsed correctly:

```
In [136]: print(open("tmp.csv").read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z

In [137]: df = pd.read_csv("tmp.csv", sep="|", thousands=",")

In [138]: df
Out[138]:
         ID    level category
0  Patient1   123000        x
1  Patient2    23000        y
2  Patient3  1234018        z

In [139]: df.level.dtype
Out[139]: dtype('int64')
```

NA values

To control which values are parsed as missing values (which are signified by `NaN`), specify a string in `na_values`. If you specify a list of strings, then all values in it are considered to be missing values. If you specify a number (a `float`, like `5.0` or an `integer` like `5`), the corresponding equivalent values will also imply a missing value (in this case effectively `[5.0, 5]` are recognized as `NaN`).

To completely override the default values that are recognized as missing, specify `keep_default_na=False`.

The default `NaN` recognized values are `['-1.#IND', '1.#QNAN', '1.#IND', '-1.#QNAN', '#N/A N/A', '#N/A', 'N/A', 'n/a', 'NA', '<NA>', '#NA', 'NULL', 'null', 'NaN', '-NaN', 'nan', '-nan', '']`.

Let us consider some examples:

```
pd.read_csv("path_to_file.csv", na_values=[5])
```

In the example above `5` and `5.0` will be recognized as `NaN`, in addition to the defaults. A string will first be interpreted as a numerical `5`, then as a `NaN`.

```
pd.read_csv("path_to_file.csv", keep_default_na=False, na_values=[""])
```

Above, only an empty field will be recognized as `NaN`.

```
pd.read_csv("path_to_file.csv", keep_default_na=False, na_values=["NA", "0"])
```

Above, both `NA` and `0` as strings are `NaN`.

```
pd.read_csv("path_to_file.csv", na_values=["Nope"])
```

The default values, in addition to the string `"Nope"` are recognized as `NaN`.

Infinity

`inf` like values will be parsed as `np.inf` (positive infinity), and `-inf` as `-np.inf` (negative infinity). These will ignore the case of the value, meaning `Inf`, will also be parsed as `np.inf`.

Returning Series

Using the `squeeze` keyword, the parser will return output with a single column as a `Series`:

```
In [140]: print(open("tmp.csv").read())
level
Patient1,123000
Patient2,23000
Patient3,1234018

In [141]: output = pd.read_csv("tmp.csv", squeeze=True)

In [142]: output
Out[142]:
Patient1     123000
Patient2      23000
Patient3    1234018
Name: level, dtype: int64

In [143]: type(output)
Out[143]: pandas.core.series.Series
```

Boolean values

The common values `True`, `False`, `TRUE`, and `FALSE` are all recognized as boolean. Occasionally you might want to recognize other values as being boolean. To do this, use the `true_values` and `false_values` options as follows:

```
In [144]: data = "a,b,c\n1,Yes,2\n3,No,4"

In [145]: print(data)
a,b,c
1,Yes,2
3,No,4

In [146]: pd.read_csv(StringIO(data))
Out[146]:
   a    b  c
0  1  Yes  2
1  3   No  4

In [147]: pd.read_csv(StringIO(data), true_values=["Yes"], false_values=["No"])
Out[147]:
   a      b  c
0  1   True  2
1  3  False  4
```

Handling "bad" lines

Some files may have malformed lines with too few fields or too many. Lines with too few fields will have NA values filled in the trailing fields. Lines with too many fields will raise an error by default:

```
In [148]: data = "a,b,c\n1,2,3\n4,5,6,7\n8,9,10"

In [149]: pd.read_csv(StringIO(data))
---------------------------------------------------------------------------
ParserError                               Traceback (most recent call last)
<ipython-input-149-6388c394e6b8> in <module>
----> 1 pd.read_csv(StringIO(data))

/pandas/pandas/io/parsers.py in read_csv(filepath_or_buffer, sep, delimiter, header,␣
↪names, index_col, usecols, squeeze, prefix, mangle_dupe_cols, dtype, engine,␣
↪converters, true_values, false_values, skipinitialspace, skiprows, skipfooter,␣
↪nrows, na_values, keep_default_na, na_filter, verbose, skip_blank_lines, parse_
↪dates, infer_datetime_format, keep_date_col, date_parser, dayfirst, cache_dates,␣
↪iterator, chunksize, compression, thousands, decimal, lineterminator, quotechar,␣
↪quoting, doublequote, escapechar, comment, encoding, dialect, error_bad_lines, warn_
↪bad_lines, delim_whitespace, low_memory, memory_map, float_precision, storage_
↪options)
    608     kwds.update(kwds_defaults)
    609
--> 610     return _read(filepath_or_buffer, kwds)
    611
    612

/pandas/pandas/io/parsers.py in _read(filepath_or_buffer, kwds)
    466
    467     with parser:
--> 468         return parser.read(nrows)
```

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```
    469
    470

/pandas/pandas/io/parsers.py in read(self, nrows)
   1055     def read(self, nrows=None):
   1056         nrows = validate_integer("nrows", nrows)
-> 1057         index, columns, col_dict = self._engine.read(nrows)
   1058
   1059         if index is None:

/pandas/pandas/io/parsers.py in read(self, nrows)
   2059     def read(self, nrows=None):
   2060         try:
-> 2061             data = self._reader.read(nrows)
   2062         except StopIteration:
   2063             if self._first_chunk:

/pandas/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader.read()

/pandas/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._read_low_memory()

/pandas/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._read_rows()

/pandas/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._tokenize_rows()

/pandas/pandas/_libs/parsers.pyx in pandas._libs.parsers.raise_parser_error()

ParserError: Error tokenizing data. C error: Expected 3 fields in line 3, saw 4
```

You can elect to skip bad lines:

```
In [29]: pd.read_csv(StringIO(data), error_bad_lines=False)
Skipping line 3: expected 3 fields, saw 4

Out[29]:
   a  b   c
0  1  2   3
1  8  9  10
```

You can also use the `usecols` parameter to eliminate extraneous column data that appear in some lines but not others:

```
In [30]: pd.read_csv(StringIO(data), usecols=[0, 1, 2])

 Out[30]:
    a  b   c
 0  1  2   3
 1  4  5   6
 2  8  9  10
```

Dialect

The `dialect` keyword gives greater flexibility in specifying the file format. By default it uses the Excel dialect but you can specify either the dialect name or a `csv.Dialect` instance.

Suppose you had data with unenclosed quotes:

```
In [150]: print(data)
label1,label2,label3
index1,"a,c,e
index2,b,d,f
```

By default, `read_csv` uses the Excel dialect and treats the double quote as the quote character, which causes it to fail when it finds a newline before it finds the closing double quote.

We can get around this using `dialect`:

```
In [151]: import csv

In [152]: dia = csv.excel()

In [153]: dia.quoting = csv.QUOTE_NONE

In [154]: pd.read_csv(StringIO(data), dialect=dia)
Out[154]:
       label1 label2 label3
index1     "a      c      e
index2      b      d      f
```

All of the dialect options can be specified separately by keyword arguments:

```
In [155]: data = "a,b,c~1,2,3~4,5,6"

In [156]: pd.read_csv(StringIO(data), lineterminator="~")
Out[156]:
   a  b  c
0  1  2  3
1  4  5  6
```

Another common dialect option is `skipinitialspace`, to skip any whitespace after a delimiter:

```
In [157]: data = "a, b, c\n1, 2, 3\n4, 5, 6"

In [158]: print(data)
a, b, c
1, 2, 3
4, 5, 6

In [159]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[159]:
   a  b  c
0  1  2  3
1  4  5  6
```

The parsers make every attempt to "do the right thing" and not be fragile. Type inference is a pretty big deal. If a column can be coerced to integer dtype without altering the contents, the parser will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

Quoting and Escape Characters

Quotes (and other escape characters) in embedded fields can be handled in any number of ways. One way is to use backslashes; to properly parse this data, you should pass the `escapechar` option:

```
In [160]: data = 'a,b\n"hello, \\"Bob\\", nice to see you",5'

In [161]: print(data)
a,b
"hello, \"Bob\", nice to see you",5

In [162]: pd.read_csv(StringIO(data), escapechar="\\")
Out[162]:
                               a  b
0  hello, "Bob", nice to see you  5
```

Files with fixed width columns

While *`read_csv()`* reads delimited data, the *`read_fwf()`* function works with data files that have known and fixed column widths. The function parameters to `read_fwf` are largely the same as `read_csv` with two extra parameters, and a different usage of the `delimiter` parameter:

- `colspecs`: A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[ ). String value 'infer' can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data. Default behavior, if not specified, is to infer.
- `widths`: A list of field widths which can be used instead of 'colspecs' if the intervals are contiguous.
- `delimiter`: Characters to consider as filler characters in the fixed-width file. Can be used to specify the filler character of the fields if it is not spaces (e.g., '~').

Consider a typical fixed-width data file:

```
In [163]: print(open("bar.csv").read())
id8141    360.242940   149.910199   11950.7
id1594    444.953632   166.985655   11788.4
id1849    364.136849   183.628767   11806.2
id1230    413.836124   184.375703   11916.8
id1948    502.953953   173.237159   12468.3
```

In order to parse this file into a `DataFrame`, we simply need to supply the column specifications to the `read_fwf` function along with the file name:

```
# Column specifications are a list of half-intervals
In [164]: colspecs = [(0, 6), (8, 20), (21, 33), (34, 43)]

In [165]: df = pd.read_fwf("bar.csv", colspecs=colspecs, header=None, index_col=0)

In [166]: df
Out[166]:
                  1           2        3
0
id8141  360.242940  149.910199  11950.7
id1594  444.953632  166.985655  11788.4
id1849  364.136849  183.628767  11806.2
id1230  413.836124  184.375703  11916.8
id1948  502.953953  173.237159  12468.3
```

Note how the parser automatically picks column names X.<column number> when `header=None` argument is specified. Alternatively, you can supply just the column widths for contiguous columns:

```
# Widths are a list of integers
In [167]: widths = [6, 14, 13, 10]

In [168]: df = pd.read_fwf("bar.csv", widths=widths, header=None)

In [169]: df
Out[169]:
        0           1           2        3
0  id8141  360.242940  149.910199  11950.7
1  id1594  444.953632  166.985655  11788.4
2  id1849  364.136849  183.628767  11806.2
3  id1230  413.836124  184.375703  11916.8
4  id1948  502.953953  173.237159  12468.3
```

The parser will take care of extra white spaces around the columns so it's ok to have extra separation between the columns in the file.

By default, `read_fwf` will try to infer the file's `colspecs` by using the first 100 rows of the file. It can do it only in cases when the columns are aligned and correctly separated by the provided `delimiter` (default delimiter is whitespace).

```
In [170]: df = pd.read_fwf("bar.csv", header=None, index_col=0)

In [171]: df
Out[171]:
                 1           2        3
0
id8141  360.242940  149.910199  11950.7
id1594  444.953632  166.985655  11788.4
id1849  364.136849  183.628767  11806.2
id1230  413.836124  184.375703  11916.8
id1948  502.953953  173.237159  12468.3
```

`read_fwf` supports the `dtype` parameter for specifying the types of parsed columns to be different from the inferred type.

```
In [172]: pd.read_fwf("bar.csv", header=None, index_col=0).dtypes
Out[172]:
1    float64
2    float64
3    float64
dtype: object

In [173]: pd.read_fwf("bar.csv", header=None, dtype={2: "object"}).dtypes
Out[173]:
0     object
1    float64
2     object
3    float64
dtype: object
```

Indexes

Files with an "implicit" index column

Consider a file with one less entry in the header than the number of data column:

```
In [174]: print(open("foo.csv").read())
A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

In this special case, `read_csv` assumes that the first column is to be used as the index of the `DataFrame`:

```
In [175]: pd.read_csv("foo.csv")
Out[175]:
           A  B  C
20090101   a  1  2
20090102   b  3  4
20090103   c  4  5
```

Note that the dates weren't automatically parsed. In that case you would need to do as before:

```
In [176]: df = pd.read_csv("foo.csv", parse_dates=True)

In [177]: df.index
Out[177]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype=
↪'datetime64[ns]', freq=None)
```

Reading an index with a `MultiIndex`

Suppose you have data indexed by two columns:

```
In [178]: print(open("data/mindex_ex.csv").read())
year,indiv,zit,xit
1977,"A",1.2,.6
1977,"B",1.5,.5
1977,"C",1.7,.8
1978,"A",.2,.06
1978,"B",.7,.2
1978,"C",.8,.3
1978,"D",.9,.5
1978,"E",1.4,.9
1979,"C",.2,.15
1979,"D",.14,.05
1979,"E",.5,.15
1979,"F",1.2,.5
1979,"G",3.4,1.9
1979,"H",5.4,2.7
1979,"I",6.4,1.2
```

The `index_col` argument to `read_csv` can take a list of column numbers to turn multiple columns into a `MultiIndex` for the index of the returned object:

```
In [179]: df = pd.read_csv("data/mindex_ex.csv", index_col=[0, 1])

In [180]: df
Out[180]:
              zit   xit
year indiv
1977 A       1.20  0.60
     B       1.50  0.50
     C       1.70  0.80
1978 A       0.20  0.06
     B       0.70  0.20
     C       0.80  0.30
     D       0.90  0.50
     E       1.40  0.90
1979 C       0.20  0.15
     D       0.14  0.05
     E       0.50  0.15
     F       1.20  0.50
     G       3.40  1.90
     H       5.40  2.70
     I       6.40  1.20

In [181]: df.loc[1978]
Out[181]:
        zit   xit
indiv
A       0.2  0.06
B       0.7  0.20
C       0.8  0.30
D       0.9  0.50
E       1.4  0.90
```

Reading columns with a `MultiIndex`

By specifying list of row locations for the `header` argument, you can read in a `MultiIndex` for the columns. Specifying non-consecutive rows will skip the intervening rows.

```
In [182]: from pandas._testing import makeCustomDataframe as mkdf

In [183]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)

In [184]: df.to_csv("mi.csv")

In [185]: print(open("mi.csv").read())
C0,,C_l0_g0,C_l0_g1,C_l0_g2
C1,,C_l1_g0,C_l1_g1,C_l1_g2
C2,,C_l2_g0,C_l2_g1,C_l2_g2
C3,,C_l3_g0,C_l3_g1,C_l3_g2
R0,R1,,,
R_l0_g0,R_l1_g0,R0C0,R0C1,R0C2
R_l0_g1,R_l1_g1,R1C0,R1C1,R1C2
R_l0_g2,R_l1_g2,R2C0,R2C1,R2C2
R_l0_g3,R_l1_g3,R3C0,R3C1,R3C2
R_l0_g4,R_l1_g4,R4C0,R4C1,R4C2
```

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```
In [186]: pd.read_csv("mi.csv", header=[0, 1, 2, 3], index_col=[0, 1])
Out[186]:
C0              C_l0_g0 C_l0_g1 C_l0_g2
C1              C_l1_g0 C_l1_g1 C_l1_g2
C2              C_l2_g0 C_l2_g1 C_l2_g2
C3              C_l3_g0 C_l3_g1 C_l3_g2
R0      R1
R_l0_g0 R_l1_g0    R0C0    R0C1    R0C2
R_l0_g1 R_l1_g1    R1C0    R1C1    R1C2
R_l0_g2 R_l1_g2    R2C0    R2C1    R2C2
R_l0_g3 R_l1_g3    R3C0    R3C1    R3C2
R_l0_g4 R_l1_g4    R4C0    R4C1    R4C2
```

`read_csv` is also able to interpret a more common format of multi-columns indices.

```
In [187]: print(open("mi2.csv").read())
,a,a,a,b,c,c
,q,r,s,t,u,v
one,1,2,3,4,5,6
two,7,8,9,10,11,12

In [188]: pd.read_csv("mi2.csv", header=[0, 1], index_col=0)
Out[188]:
     a         b    c
     q  r  s   t   u   v
one  1  2  3   4   5   6
two  7  8  9  10  11  12
```

Note: If an `index_col` is not specified (e.g. you don't have an index, or wrote it with `df.to_csv(..., index=False)`, then any `names` on the columns index will be *lost*.

Automatically "sniffing" the delimiter

`read_csv` is capable of inferring delimited (not necessarily comma-separated) files, as pandas uses the `csv.Sniffer` class of the csv module. For this, you have to specify `sep=None`.

```
In [189]: print(open("tmp2.sv").read())
:0:1:2:3
0:0.4691122999071863:-0.2828633443286633:-1.5090585031735124:-1.1356323710171934
1:1.2121120250208506:-0.17321464905330858:0.11920871129693428:-1.0442359662799567
2:-0.8618489633477999:-2.1045692188948086:-0.4949292740687813:1.071803807037338
3:0.7215551622443669:-0.7067711336300845:-1.0395749851146963:0.27185988554282986
4:-0.42497232978883753:0.567020349793672:0.27623201927771873:-1.0874006912859915
5:-0.6736897080883706:0.1136484096888855:-1.4784265524372235:0.5249876671147047
6:0.4047052186802365:0.5770459859204836:-1.7150020161146375:-1.0392684835147725
7:-0.3706468582364464:-1.1578922506419993:-1.344311812731667:0.8448851414248841
8:1.0757697837155533:-0.10904997528022223:1.6435630703622064:-1.4693879595399115
9:0.35702056413309086:-0.6746001037299882:-1.776903716971867:-0.9689138124473498


In [190]: pd.read_csv("tmp2.sv", sep=None, engine="python")
Out[190]:
   Unnamed: 0         0         1         2         3
0           0  0.469112 -0.282863 -1.509059 -1.135632
```

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```
1           1  1.212112 -0.173215  0.119209 -1.044236
2           2 -0.861849 -2.104569 -0.494929  1.071804
3           3  0.721555 -0.706771 -1.039575  0.271860
4           4 -0.424972  0.567020  0.276232 -1.087401
5           5 -0.673690  0.113648 -1.478427  0.524988
6           6  0.404705  0.577046 -1.715002 -1.039268
7           7 -0.370647 -1.157892 -1.344312  0.844885
8           8  1.075770 -0.109050  1.643563 -1.469388
9           9  0.357021 -0.674600 -1.776904 -0.968914
```

Reading multiple files to create a single DataFrame

It's best to use `concat()` to combine multiple files. See the *cookbook* for an example.

Iterating through files chunk by chunk

Suppose you wish to iterate through a (potentially very large) file lazily rather than reading the entire file into memory, such as the following:

```
In [191]: print(open("tmp.sv").read())
|0|1|2|3
0|0.4691122999071863|-0.2828633443286633|-1.5090585031735124|-1.1356323710171934
1|1.2121120250208506|-0.17321464905330858|0.11920871129693428|-1.0442359662799567
2|-0.8618489633477999|-2.1045692188948086|-0.4949292740687813|1.071803807037338
3|0.7215551622443669|-0.7067711336300845|-1.0395749851146963|0.27185988554282986
4|-0.42497232978883753|0.567020349793672|0.27623201927771873|-1.0874006912859915
5|-0.6736897080883706|0.1136484096888855|-1.4784265524372235|0.5249876671147047
6|0.40470521868023 65|0.5770459859204836|-1.7150020161146375|-1.0392684835147725
7|-0.3706468582364464|-1.1578922506419993|-1.344311812731667|0.8448851414248841
8|1.0757697837155533|-0.10904997528022223|1.6435630703622064|-1.4693879595399115
9|0.35702056413309086|-0.6746001037299882|-1.776903716971867|-0.9689138124473498


In [192]: table = pd.read_csv("tmp.sv", sep="|")

In [193]: table
Out[193]:
   Unnamed: 0         0         1         2         3
0           0  0.469112 -0.282863 -1.509059 -1.135632
1           1  1.212112 -0.173215  0.119209 -1.044236
2           2 -0.861849 -2.104569 -0.494929  1.071804
3           3  0.721555 -0.706771 -1.039575  0.271860
4           4 -0.424972  0.567020  0.276232 -1.087401
5           5 -0.673690  0.113648 -1.478427  0.524988
6           6  0.404705  0.577046 -1.715002 -1.039268
7           7 -0.370647 -1.157892 -1.344312  0.844885
8           8  1.075770 -0.109050  1.643563 -1.469388
9           9  0.357021 -0.674600 -1.776904 -0.968914
```

By specifying a `chunksize` to `read_csv`, the return value will be an iterable object of type `TextFileReader`:

```
In [194]: with pd.read_csv("tmp.sv", sep="|", chunksize=4) as reader:
   .....:     reader
   .....:     for chunk in reader:
```

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```
   .....:         print(chunk)
   .....:
   Unnamed: 0         0         1         2         3
0           0  0.469112 -0.282863 -1.509059 -1.135632
1           1  1.212112 -0.173215  0.119209 -1.044236
2           2 -0.861849 -2.104569 -0.494929  1.071804
3           3  0.721555 -0.706771 -1.039575  0.271860
   Unnamed: 0         0         1         2         3
4           4 -0.424972  0.567020  0.276232 -1.087401
5           5 -0.673690  0.113648 -1.478427  0.524988
6           6  0.404705  0.577046 -1.715002 -1.039268
7           7 -0.370647 -1.157892 -1.344312  0.844885
   Unnamed: 0         0        1         2         3
8           8  1.075770 -0.10905  1.643563 -1.469388
9           9  0.357021 -0.67460 -1.776904 -0.968914
```

Changed in version 1.2: `read_csv/json/sas` return a context-manager when iterating through a file.

Specifying `iterator=True` will also return the `TextFileReader` object:

```
In [195]: with pd.read_csv("tmp.sv", sep="|", iterator=True) as reader:
   .....:     reader.get_chunk(5)
   .....:
```

Specifying the parser engine

Under the hood pandas uses a fast and efficient parser implemented in C as well as a Python implementation which is currently more feature-complete. Where possible pandas uses the C parser (specified as `engine='c'`), but may fall back to Python if C-unsupported options are specified. Currently, C-unsupported options include:

- `sep` other than a single character (e.g. regex separators)
- `skipfooter`
- `sep=None` with `delim_whitespace=False`

Specifying any of the above options will produce a `ParserWarning` unless the python engine is selected explicitly using `engine='python'`.

Reading/writing remote files

You can pass in a URL to read or write remote files to many of pandas' IO functions - the following example shows reading a CSV file:

```
df = pd.read_csv("https://download.bls.gov/pub/time.series/cu/cu.item", sep="\t")
```

All URLs which are not local files or HTTP(s) are handled by fsspec, if installed, and its various filesystem implementations (including Amazon S3, Google Cloud, SSH, FTP, webHDFS...). Some of these implementations will require additional packages to be installed, for example S3 URLs require the s3fs library:

```
df = pd.read_json("s3://pandas-test/adatafile.json")
```

When dealing with remote storage systems, you might need extra configuration with environment variables or config files in special locations. For example, to access data in your S3 bucket, you will need to define credentials in one of the several ways listed in the S3Fs documentation. The same is true for several of the storage backends, and you

should follow the links at fsimpl1 for implementations built into `fsspec` and fsimpl2 for those not included in the main `fsspec` distribution.

You can also pass parameters directly to the backend driver. For example, if you do *not* have S3 credentials, you can still access public data by specifying an anonymous connection, such as

New in version 1.2.0.

```
pd.read_csv(
    "s3://ncei-wcsd-archive/data/processed/SH1305/18kHz/SaKe2013"
    "-D20130523-T080854_to_SaKe2013-D20130523-T085643.csv",
    storage_options={"anon": True},
)
```

`fsspec` also allows complex URLs, for accessing data in compressed archives, local caching of files, and more. To locally cache the above example, you would modify the call to

```
pd.read_csv(
    "simplecache::s3://ncei-wcsd-archive/data/processed/SH1305/18kHz/"
    "SaKe2013-D20130523-T080854_to_SaKe2013-D20130523-T085643.csv",
    storage_options={"s3": {"anon": True}},
)
```

where we specify that the "anon" parameter is meant for the "s3" part of the implementation, not to the caching implementation. Note that this caches to a temporary directory for the duration of the session only, but you can also specify a permanent store.

Writing out data

Writing to CSV format

The `Series` and `DataFrame` objects have an instance method `to_csv` which allows storing the contents of the object as a comma-separated-values file. The function takes a number of arguments. Only the first is required.

- `path_or_buf`: A string path to the file to write or a file object. If a file object it must be opened with `newline=''`
- `sep` : Field delimiter for the output file (default ",")
- `na_rep`: A string representation of a missing value (default '')
- `float_format`: Format string for floating point numbers
- `columns`: Columns to write (default None)
- `header`: Whether to write out the column names (default True)
- `index`: whether to write row (index) names (default True)
- `index_label`: Column label(s) for index column(s) if desired. If None (default), and `header` and `index` are True, then the index names are used. (A sequence should be given if the `DataFrame` uses MultiIndex).
- `mode` : Python write mode, default 'w'
- `encoding`: a string representing the encoding to use if the contents are non-ASCII, for Python versions prior to 3
- `line_terminator`: Character sequence denoting line end (default `os.linesep`)

- `quoting`: Set quoting rules as in csv module (default csv.QUOTE_MINIMAL). Note that if you have set a `float_format` then floats are converted to strings and csv.QUOTE_NONNUMERIC will treat them as non-numeric
- `quotechar`: Character used to quote fields (default '"')
- `doublequote`: Control quoting of `quotechar` in fields (default True)
- `escapechar`: Character used to escape `sep` and `quotechar` when appropriate (default None)
- `chunksize`: Number of rows to write at a time
- `date_format`: Format string for datetime objects

Writing a formatted string

The `DataFrame` object has an instance method `to_string` which allows control over the string representation of the object. All arguments are optional:

- `buf` default None, for example a StringIO object
- `columns` default None, which columns to write
- `col_space` default None, minimum width of each column.
- `na_rep` default `NaN`, representation of NA value
- `formatters` default None, a dictionary (by column) of functions each of which takes a single argument and returns a formatted string
- `float_format` default None, a function which takes a single (float) argument and returns a formatted string; to be applied to floats in the `DataFrame`.
- `sparsify` default True, set to False for a `DataFrame` with a hierarchical index to print every MultiIndex key at each row.
- `index_names` default True, will print the names of the indices
- `index` default True, will print the index (ie, row labels)
- `header` default True, will print the column labels
- `justify` default `left`, will print column headers left- or right-justified

The `Series` object also has a `to_string` method, but with only the `buf`, `na_rep`, `float_format` arguments. There is also a `length` argument which, if set to `True`, will additionally output the length of the Series.

2.4.2 JSON

Read and write `JSON` format files and strings.

Writing JSON

A `Series` or `DataFrame` can be converted to a valid JSON string. Use `to_json` with optional parameters:

- `path_or_buf` : the pathname or buffer to write the output This can be `None` in which case a JSON string is returned
- `orient` :

  `Series`:

  - default is `index`
  - allowed values are {`split`, `records`, `index`}

  `DataFrame`:

  - default is `columns`
  - allowed values are {`split`, `records`, `index`, `columns`, `values`, `table`}

  The format of the JSON string

`split`	dict like {index -> [index], columns -> [columns], data -> [values]}
`records`	list like [{column -> value}, ... , {column -> value}]
`index`	dict like {index -> {column -> value}}
`columns`	dict like {column -> {index -> value}}
`values`	just the values array

- `date_format` : string, type of date conversion, 'epoch' for timestamp, 'iso' for ISO8601.
- `double_precision` : The number of decimal places to use when encoding floating point values, default 10.
- `force_ascii` : force encoded string to be ASCII, default True.
- `date_unit` : The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us' or 'ns' for seconds, milliseconds, microseconds and nanoseconds respectively. Default 'ms'.
- `default_handler` : The handler to call if an object cannot otherwise be converted to a suitable format for JSON. Takes a single argument, which is the object to convert, and returns a serializable object.
- `lines` : If `records` orient, then will write each record per line as json.

Note `NaN`'s, `NaT`'s and `None` will be converted to `null` and `datetime` objects will be converted based on the `date_format` and `date_unit` parameters.

```
In [196]: dfj = pd.DataFrame(np.random.randn(5, 2), columns=list("AB"))

In [197]: json = dfj.to_json()

In [198]: json
Out[198]: '{"A":{"0":-1.2945235903,"1":0.2766617129,"2":-0.0139597524,"3":-0.
↪0061535699,"4":0.8957173022},"B":{"0":0.4137381054,"1":-0.472034511,"2":-0.
↪3625429925,"3":-0.923060654,"4":0.8052440254}}'
```

Orient options

There are a number of different options for the format of the resulting JSON file / string. Consider the following `DataFrame` and `Series`:

```
In [199]: dfjo = pd.DataFrame(
   .....:     dict(A=range(1, 4), B=range(4, 7), C=range(7, 10)),
   .....:     columns=list("ABC"),
   .....:     index=list("xyz"),
   .....: )
   .....:

In [200]: dfjo
Out[200]:
   A  B  C
x  1  4  7
y  2  5  8
z  3  6  9

In [201]: sjo = pd.Series(dict(x=15, y=16, z=17), name="D")

In [202]: sjo
Out[202]:
x    15
y    16
z    17
Name: D, dtype: int64
```

Column oriented (the default for `DataFrame`) serializes the data as nested JSON objects with column labels acting as the primary index:

```
In [203]: dfjo.to_json(orient="columns")
Out[203]: '{"A":{"x":1,"y":2,"z":3},"B":{"x":4,"y":5,"z":6},"C":{"x":7,"y":8,"z":9}}'

# Not available for Series
```

Index oriented (the default for `Series`) similar to column oriented but the index labels are now primary:

```
In [204]: dfjo.to_json(orient="index")
Out[204]: '{"x":{"A":1,"B":4,"C":7},"y":{"A":2,"B":5,"C":8},"z":{"A":3,"B":6,"C":9}}'

In [205]: sjo.to_json(orient="index")
Out[205]: '{"x":15,"y":16,"z":17}'
```

Record oriented serializes the data to a JSON array of column -> value records, index labels are not included. This is useful for passing `DataFrame` data to plotting libraries, for example the JavaScript library `d3.js`:

```
In [206]: dfjo.to_json(orient="records")
Out[206]: '[{"A":1,"B":4,"C":7},{"A":2,"B":5,"C":8},{"A":3,"B":6,"C":9}]'

In [207]: sjo.to_json(orient="records")
Out[207]: '[15,16,17]'
```

Value oriented is a bare-bones option which serializes to nested JSON arrays of values only, column and index labels are not included:

```
In [208]: dfjo.to_json(orient="values")
Out[208]: '[[1,4,7],[2,5,8],[3,6,9]]'

# Not available for Series
```

Split oriented serializes to a JSON object containing separate entries for values, index and columns. Name is also included for `Series`:

```
In [209]: dfjo.to_json(orient="split")
Out[209]: '{"columns":["A","B","C"],"index":["x","y","z"],"data":[[1,4,7],[2,5,8],[3,
↪6,9]]}'

In [210]: sjo.to_json(orient="split")
Out[210]: '{"name":"D","index":["x","y","z"],"data":[15,16,17]}'
```

Table oriented serializes to the JSON Table Schema, allowing for the preservation of metadata including but not limited to dtypes and index names.

Note: Any orient option that encodes to a JSON object will not preserve the ordering of index and column labels during round-trip serialization. If you wish to preserve label ordering use the `split` option as it uses ordered containers.

Date handling

Writing in ISO date format:

```
In [211]: dfd = pd.DataFrame(np.random.randn(5, 2), columns=list("AB"))

In [212]: dfd["date"] = pd.Timestamp("20130101")

In [213]: dfd = dfd.sort_index(1, ascending=False)

In [214]: json = dfd.to_json(date_format="iso")

In [215]: json
Out[215]: '{"date":{"0":"2013-01-01T00:00:00.000Z","1":"2013-01-01T00:00:00.000Z","2":
↪"2013-01-01T00:00:00.000Z","3":"2013-01-01T00:00:00.000Z","4":"2013-01-01T00:00:00.
↪000Z"},"B":{"0":2.5656459463,"1":1.3403088498,"2":-0.2261692849,"3":0.8138502857,"4
↪":-0.8273169356},"A":{"0":-1.2064117817,"1":1.4312559863,"2":-1.1702987971,"3":0.
↪4108345112,"4":0.1320031703}}'
```

Writing in ISO date format, with microseconds:

```
In [216]: json = dfd.to_json(date_format="iso", date_unit="us")

In [217]: json
Out[217]: '{"date":{"0":"2013-01-01T00:00:00.000000Z","1":"2013-01-01T00:00:00.000000Z
↪","2":"2013-01-01T00:00:00.000000Z","3":"2013-01-01T00:00:00.000000Z","4":"2013-01-
↪01T00:00:00.000000Z"},"B":{"0":2.5656459463,"1":1.3403088498,"2":-0.2261692849,"3":
↪0.8138502857,"4":-0.8273169356},"A":{"0":-1.2064117817,"1":1.4312559863,"2":-1.
↪1702987971,"3":0.4108345112,"4":0.1320031703}}'
```

Epoch timestamps, in seconds:

```
In [218]: json = dfd.to_json(date_format="epoch", date_unit="s")

In [219]: json
Out[219]: '{"date":{"0":1356998400,"1":1356998400,"2":1356998400,"3":1356998400,"4":
↪1356998400},"B":{"0":2.5656459463,"1":1.3403088498,"2":-0.2261692849,"3":0.
↪8138502857,"4":-0.8273169356},"A":{"0":-1.2064117817,"1":1.4312559863,"2":-1.
↪1702987971,"3":0.4108345112,"4":0.1320031703}}'
```

Writing to a file, with a date index and a date column:

```
In [220]: dfj2 = dfj.copy()

In [221]: dfj2["date"] = pd.Timestamp("20130101")

In [222]: dfj2["ints"] = list(range(5))

In [223]: dfj2["bools"] = True

In [224]: dfj2.index = pd.date_range("20130101", periods=5)

In [225]: dfj2.to_json("test.json")

In [226]: with open("test.json") as fh:
   .....:     print(fh.read())
   .....:
{"A":{"1356998400000":-1.2945235903,"1357084800000":0.2766617129,"1357171200000":-0.
↪0139597524,"1357257600000":-0.0061535699,"1357344000000":0.8957173022},"B":{
↪"1356998400000":0.4137381054,"1357084800000":-0.472034511,"1357171200000":-0.
↪3625429925,"1357257600000":-0.923060654,"1357344000000":0.8052440254},"date":{
↪"1356998400000":1356998400000,"1357084800000":1356998400000,"1357171200000":
↪1356998400000,"1357257600000":1356998400000,"1357344000000":1356998400000},"ints":{
↪"1356998400000":0,"1357084800000":1,"1357171200000":2,"1357257600000":3,
↪"1357344000000":4},"bools":{"1356998400000":true,"1357084800000":true,"1357171200000
↪":true,"1357257600000":true,"1357344000000":true}}
```

Fallback behavior

If the JSON serializer cannot handle the container contents directly it will fall back in the following manner:

- if the dtype is unsupported (e.g. `np.complex_`) then the `default_handler`, if provided, will be called for each value, otherwise an exception is raised.
- if an object is unsupported it will attempt the following:
  - check if the object has defined a `toDict` method and call it. A `toDict` method should return a `dict` which will then be JSON serialized.
  - invoke the `default_handler` if one was provided.
  - convert the object to a `dict` by traversing its contents. However this will often fail with an `OverflowError` or give unexpected results.

In general the best approach for unsupported objects or dtypes is to provide a `default_handler`. For example:

```
>>> DataFrame([1.0, 2.0, complex(1.0, 2.0)]).to_json()  # raises
RuntimeError: Unhandled numpy dtype 15
```

can be dealt with by specifying a simple `default_handler`:

```
In [227]: pd.DataFrame([1.0, 2.0, complex(1.0, 2.0)]).to_json(default_handler=str)
Out[227]: '{"0":{"0":"(1+0j)","1":"(2+0j)","2":"(1+2j)"}}'
```

Reading JSON

Reading a JSON string to pandas object can take a number of parameters. The parser will try to parse a `DataFrame` if `typ` is not supplied or is `None`. To explicitly force `Series` parsing, pass `typ=series`

- `filepath_or_buffer` : a **VALID** JSON string or file handle / StringIO. The string could be a URL. Valid URL schemes include http, ftp, S3, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.json
- `typ` : type of object to recover (series or frame), default 'frame'
- `orient` :

  Series :

  - default is `index`
  - allowed values are {`split`, `records`, `index`}

  DataFrame

  - default is `columns`
  - allowed values are {`split`, `records`, `index`, `columns`, `values`, `table`}

  The format of the JSON string

`split`	dict like {index -> [index], columns -> [columns], data -> [values]}
`records`	list like [{column -> value}, ... , {column -> value}]
`index`	dict like {index -> {column -> value}}
`columns`	dict like {column -> {index -> value}}
`values`	just the values array
`table`	adhering to the JSON Table Schema

- `dtype` : if True, infer dtypes, if a dict of column to dtype, then use those, if `False`, then don't infer dtypes at all, default is True, apply only to the data.
- `convert_axes` : boolean, try to convert the axes to the proper dtypes, default is `True`
- `convert_dates` : a list of columns to parse for dates; If `True`, then try to parse date-like columns, default is `True`.
- `keep_default_dates` : boolean, default `True`. If parsing dates, then parse the default date-like columns.
- `numpy` : direct decoding to NumPy arrays. default is `False`; Supports numeric data only, although labels may be non-numeric. Also note that the JSON ordering **MUST** be the same for each term if `numpy=True`.
- `precise_float` : boolean, default `False`. Set to enable usage of higher precision (strtod) function when decoding string to double values. Default (`False`) is to use fast but less precise builtin functionality.
- `date_unit` : string, the timestamp unit to detect if converting dates. Default None. By default the timestamp precision will be detected, if this is not desired then pass one of 's', 'ms', 'us' or 'ns' to force timestamp precision to seconds, milliseconds, microseconds or nanoseconds respectively.
- `lines` : reads file as one json object per line.
- `encoding` : The encoding to use to decode py3 bytes.

- `chunksize` : when used in combination with `lines=True`, return a JsonReader which reads in `chunksize` lines per iteration.

The parser will raise one of `ValueError/TypeError/AssertionError` if the JSON is not parseable.

If a non-default `orient` was used when encoding to JSON be sure to pass the same option here so that decoding produces sensible results, see *Orient Options* for an overview.

Data conversion

The default of `convert_axes=True`, `dtype=True`, and `convert_dates=True` will try to parse the axes, and all of the data into appropriate types, including dates. If you need to override specific dtypes, pass a dict to `dtype`. `convert_axes` should only be set to `False` if you need to preserve string-like numbers (e.g. '1', '2') in an axes.

Note: Large integer values may be converted to dates if `convert_dates=True` and the data and / or column labels appear 'date-like'. The exact threshold depends on the `date_unit` specified. 'date-like' means that the column label meets one of the following criteria:

- it ends with `'_at'`
- it ends with `'_time'`
- it begins with `'timestamp'`
- it is `'modified'`
- it is `'date'`

Warning: When reading JSON data, automatic coercing into dtypes has some quirks:

- an index can be reconstructed in a different order from serialization, that is, the returned order is not guaranteed to be the same as before serialization
- a column that was `float` data will be converted to `integer` if it can be done safely, e.g. a column of `1.`
- bool columns will be converted to `integer` on reconstruction

Thus there are times where you may want to specify specific dtypes via the `dtype` keyword argument.

Reading from a JSON string:

```
In [228]: pd.read_json(json)
Out[228]:
        date          B         A
0 2013-01-01  2.565646 -1.206412
1 2013-01-01  1.340309  1.431256
2 2013-01-01 -0.226169 -1.170299
3 2013-01-01  0.813850  0.410835
4 2013-01-01 -0.827317  0.132003
```

Reading from a file:

```
In [229]: pd.read_json("test.json")
Out[229]:
                   A         B       date  ints  bools
2013-01-01 -1.294524  0.413738 2013-01-01     0   True
```

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```
2013-01-02  0.276662 -0.472035 2013-01-01      1    True
2013-01-03 -0.013960 -0.362543 2013-01-01      2    True
2013-01-04 -0.006154 -0.923061 2013-01-01      3    True
2013-01-05  0.895717  0.805244 2013-01-01      4    True
```

Don't convert any data (but still convert axes and dates):

```
In [230]: pd.read_json("test.json", dtype=object).dtypes
Out[230]:
A        object
B        object
date     object
ints     object
bools    object
dtype: object
```

Specify dtypes for conversion:

```
In [231]: pd.read_json("test.json", dtype={"A": "float32", "bools": "int8"}).dtypes
Out[231]:
A               float32
B               float64
date     datetime64[ns]
ints              int64
bools              int8
dtype: object
```

Preserve string indices:

```
In [232]: si = pd.DataFrame(
   .....:     np.zeros((4, 4)), columns=list(range(4)), index=[str(i) for i in␣
↪range(4)]
   .....: )
   .....:

In [233]: si
Out[233]:
     0    1    2    3
0  0.0  0.0  0.0  0.0
1  0.0  0.0  0.0  0.0
2  0.0  0.0  0.0  0.0
3  0.0  0.0  0.0  0.0

In [234]: si.index
Out[234]: Index(['0', '1', '2', '3'], dtype='object')

In [235]: si.columns
Out[235]: Int64Index([0, 1, 2, 3], dtype='int64')

In [236]: json = si.to_json()

In [237]: sij = pd.read_json(json, convert_axes=False)

In [238]: sij
Out[238]:
   0  1  2  3
0  0  0  0  0
```

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```
1  0  0  0  0
2  0  0  0  0
3  0  0  0  0

In [239]: sij.index
Out[239]: Index(['0', '1', '2', '3'], dtype='object')

In [240]: sij.columns
Out[240]: Index(['0', '1', '2', '3'], dtype='object')
```

Dates written in nanoseconds need to be read back in nanoseconds:

```
In [241]: json = dfj2.to_json(date_unit="ns")

# Try to parse timestamps as milliseconds -> Won't Work
In [242]: dfju = pd.read_json(json, date_unit="ms")

In [243]: dfju
Out[243]:
                            A         B                 date  ints  bools
1356998400000000000 -1.294524  0.413738  1356998400000000000     0   True
1357084800000000000  0.276662 -0.472035  1356998400000000000     1   True
1357171200000000000 -0.013960 -0.362543  1356998400000000000     2   True
1357257600000000000 -0.006154 -0.923061  1356998400000000000     3   True
1357344000000000000  0.895717  0.805244  1356998400000000000     4   True

# Let pandas detect the correct precision
In [244]: dfju = pd.read_json(json)

In [245]: dfju
Out[245]:
                   A         B       date  ints  bools
2013-01-01 -1.294524  0.413738 2013-01-01     0   True
2013-01-02  0.276662 -0.472035 2013-01-01     1   True
2013-01-03 -0.013960 -0.362543 2013-01-01     2   True
2013-01-04 -0.006154 -0.923061 2013-01-01     3   True
2013-01-05  0.895717  0.805244 2013-01-01     4   True

# Or specify that all timestamps are in nanoseconds
In [246]: dfju = pd.read_json(json, date_unit="ns")

In [247]: dfju
Out[247]:
                   A         B       date  ints  bools
2013-01-01 -1.294524  0.413738 2013-01-01     0   True
2013-01-02  0.276662 -0.472035 2013-01-01     1   True
2013-01-03 -0.013960 -0.362543 2013-01-01     2   True
2013-01-04 -0.006154 -0.923061 2013-01-01     3   True
2013-01-05  0.895717  0.805244 2013-01-01     4   True
```

The Numpy parameter

Note: This param has been deprecated as of version 1.0.0 and will raise a `FutureWarning`.

This supports numeric data only. Index and columns labels may be non-numeric, e.g. strings, dates etc.

If `numpy=True` is passed to `read_json` an attempt will be made to sniff an appropriate dtype during deserialization and to subsequently decode directly to NumPy arrays, bypassing the need for intermediate Python objects.

This can provide speedups if you are deserialising a large amount of numeric data:

```
In [248]: randfloats = np.random.uniform(-100, 1000, 10000)

In [249]: randfloats.shape = (1000, 10)

In [250]: dffloats = pd.DataFrame(randfloats, columns=list("ABCDEFGHIJ"))

In [251]: jsonfloats = dffloats.to_json()
```

```
In [252]: %timeit pd.read_json(jsonfloats)
7.6 ms +- 85.9 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [253]: %timeit pd.read_json(jsonfloats, numpy=True)
5.39 ms +- 20.3 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

The speedup is less noticeable for smaller datasets:

```
In [254]: jsonfloats = dffloats.head(100).to_json()
```

```
In [255]: %timeit pd.read_json(jsonfloats)
5.18 ms +- 47.2 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [256]: %timeit pd.read_json(jsonfloats, numpy=True)
4.41 ms +- 36.8 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Warning: Direct NumPy decoding makes a number of assumptions and may fail or produce unexpected output if these assumptions are not satisfied:

- data is numeric.
- data is uniform. The dtype is sniffed from the first value decoded. A `ValueError` may be raised, or incorrect output may be produced if this condition is not satisfied.
- labels are ordered. Labels are only read from the first container, it is assumed that each subsequent row / column has been encoded in the same order. This should be satisfied if the data was encoded using `to_json` but may not be the case if the JSON is from another source.

Normalization

pandas provides a utility function to take a dict or list of dicts and *normalize* this semi-structured data into a flat table.

```
In [257]: data = [
   .....:     {"id": 1, "name": {"first": "Coleen", "last": "Volk"}},
   .....:     {"name": {"given": "Mose", "family": "Regner"}},
   .....:     {"id": 2, "name": "Faye Raker"},
   .....: ]
   .....:

In [258]: pd.json_normalize(data)
Out[258]:
    id name.first name.last name.given name.family        name
0  1.0     Coleen      Volk        NaN         NaN         NaN
1  NaN        NaN       NaN       Mose      Regner         NaN
2  2.0        NaN       NaN        NaN         NaN  Faye Raker
```

```
In [259]: data = [
   .....:     {
   .....:         "state": "Florida",
   .....:         "shortname": "FL",
   .....:         "info": {"governor": "Rick Scott"},
   .....:         "county": [
   .....:             {"name": "Dade", "population": 12345},
   .....:             {"name": "Broward", "population": 40000},
   .....:             {"name": "Palm Beach", "population": 60000},
   .....:         ],
   .....:     },
   .....:     {
   .....:         "state": "Ohio",
   .....:         "shortname": "OH",
   .....:         "info": {"governor": "John Kasich"},
   .....:         "county": [
   .....:             {"name": "Summit", "population": 1234},
   .....:             {"name": "Cuyahoga", "population": 1337},
   .....:         ],
   .....:     },
   .....: ]
   .....:

In [260]: pd.json_normalize(data, "county", ["state", "shortname", ["info", "governor
↪"]])
Out[260]:
         name  population    state shortname info.governor
0        Dade       12345  Florida        FL    Rick Scott
1     Broward       40000  Florida        FL    Rick Scott
2  Palm Beach       60000  Florida        FL    Rick Scott
3      Summit        1234     Ohio        OH   John Kasich
4    Cuyahoga        1337     Ohio        OH   John Kasich
```

The max_level parameter provides more control over which level to end normalization. With max_level=1 the following snippet normalizes until 1st nesting level of the provided dict.

```
In [261]: data = [
   .....:     {
   .....:         "CreatedBy": {"Name": "User001"},
```

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```
   .....:         "Lookup": {
   .....:             "TextField": "Some text",
   .....:             "UserField": {"Id": "ID001", "Name": "Name001"},
   .....:         },
   .....:         "Image": {"a": "b"},
   .....:     }
   .....: ]
   .....:

In [262]: pd.json_normalize(data, max_level=1)
Out[262]:
  CreatedBy.Name Lookup.TextField                    Lookup.UserField Image.a
0        User001        Some text  {'Id': 'ID001', 'Name': 'Name001'}       b
```

Line delimited json

pandas is able to read and write line-delimited json files that are common in data processing pipelines using Hadoop or Spark.

For line-delimited json files, pandas can also return an iterator which reads in `chunksize` lines at a time. This can be useful for large files or to read from a stream.

```
In [263]: jsonl = """
   .....:     {"a": 1, "b": 2}
   .....:     {"a": 3, "b": 4}
   .....: """
   .....:

In [264]: df = pd.read_json(jsonl, lines=True)

In [265]: df
Out[265]:
   a  b
0  1  2
1  3  4

In [266]: df.to_json(orient="records", lines=True)
Out[266]: '{"a":1,"b":2}\n{"a":3,"b":4}\n'

# reader is an iterator that returns ``chunksize`` lines each iteration
In [267]: with pd.read_json(StringIO(jsonl), lines=True, chunksize=1) as reader:
   .....:     reader
   .....:     for chunk in reader:
   .....:         print(chunk)
   .....:
Empty DataFrame
Columns: []
Index: []
   a  b
0  1  2
   a  b
1  3  4
```

Table schema

Table Schema is a spec for describing tabular datasets as a JSON object. The JSON includes information on the field names, types, and other attributes. You can use the orient `table` to build a JSON string with two fields, `schema` and `data`.

```
In [268]: df = pd.DataFrame(
   .....:     {
   .....:         "A": [1, 2, 3],
   .....:         "B": ["a", "b", "c"],
   .....:         "C": pd.date_range("2016-01-01", freq="d", periods=3),
   .....:     },
   .....:     index=pd.Index(range(3), name="idx"),
   .....: )
   .....:

In [269]: df
Out[269]:
     A  B          C
idx
0    1  a 2016-01-01
1    2  b 2016-01-02
2    3  c 2016-01-03

In [270]: df.to_json(orient="table", date_format="iso")
Out[270]: '{"schema":{"fields":[{"name":"idx","type":"integer"},{"name":"A","type":
↪"integer"},{"name":"B","type":"string"},{"name":"C","type":"datetime"}],"primaryKey
↪":["idx"],"pandas_version":"0.20.0"},"data":[{"idx":0,"A":1,"B":"a","C":"2016-01-
↪01T00:00:00.000Z"},{"idx":1,"A":2,"B":"b","C":"2016-01-02T00:00:00.000Z"},{"idx":2,
↪"A":3,"B":"c","C":"2016-01-03T00:00:00.000Z"}]}'
```

The `schema` field contains the `fields` key, which itself contains a list of column name to type pairs, including the `Index` or `MultiIndex` (see below for a list of types). The `schema` field also contains a `primaryKey` field if the (Multi)index is unique.

The second field, `data`, contains the serialized data with the `records` orient. The index is included, and any datetimes are ISO 8601 formatted, as required by the Table Schema spec.

The full list of types supported are described in the Table Schema spec. This table shows the mapping from pandas types:

pandas type	Table Schema type
int64	integer
float64	number
bool	boolean
datetime64[ns]	datetime
timedelta64[ns]	duration
categorical	any
object	str

A few notes on the generated table schema:

- The `schema` object contains a `pandas_version` field. This contains the version of pandas' dialect of the schema, and will be incremented with each revision.
- All dates are converted to UTC when serializing. Even timezone naive values, which are treated as UTC with an offset of 0.

```
In [271]: from pandas.io.json import build_table_schema

In [272]: s = pd.Series(pd.date_range("2016", periods=4))

In [273]: build_table_schema(s)
Out[273]:
{'fields': [{'name': 'index', 'type': 'integer'},
  {'name': 'values', 'type': 'datetime'}],
 'primaryKey': ['index'],
 'pandas_version': '0.20.0'}
```

- datetimes with a timezone (before serializing), include an additional field `tz` with the time zone name (e.g. `'US/Central'`).

```
In [274]: s_tz = pd.Series(pd.date_range("2016", periods=12, tz="US/Central"))

In [275]: build_table_schema(s_tz)
Out[275]:
{'fields': [{'name': 'index', 'type': 'integer'},
  {'name': 'values', 'type': 'datetime', 'tz': 'US/Central'}],
 'primaryKey': ['index'],
 'pandas_version': '0.20.0'}
```

- Periods are converted to timestamps before serialization, and so have the same behavior of being converted to UTC. In addition, periods will contain and additional field `freq` with the period's frequency, e.g. `'A-DEC'`.

```
In [276]: s_per = pd.Series(1, index=pd.period_range("2016", freq="A-DEC",␣
↪periods=4))

In [277]: build_table_schema(s_per)
Out[277]:
{'fields': [{'name': 'index', 'type': 'datetime', 'freq': 'A-DEC'},
  {'name': 'values', 'type': 'integer'}],
 'primaryKey': ['index'],
 'pandas_version': '0.20.0'}
```

- Categoricals use the `any` type and an `enum` constraint listing the set of possible values. Additionally, an `ordered` field is included:

```
In [278]: s_cat = pd.Series(pd.Categorical(["a", "b", "a"]))

In [279]: build_table_schema(s_cat)
Out[279]:
{'fields': [{'name': 'index', 'type': 'integer'},
  {'name': 'values',
   'type': 'any',
   'constraints': {'enum': ['a', 'b']},
   'ordered': False}],
 'primaryKey': ['index'],
 'pandas_version': '0.20.0'}
```

- A `primaryKey` field, containing an array of labels, is included *if the index is unique*:

```
In [280]: s_dupe = pd.Series([1, 2], index=[1, 1])

In [281]: build_table_schema(s_dupe)
Out[281]:
```

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```
{'fields': [{'name': 'index', 'type': 'integer'},
  {'name': 'values', 'type': 'integer'}],
 'pandas_version': '0.20.0'}
```

- The `primaryKey` behavior is the same with MultiIndexes, but in this case the `primaryKey` is an array:

```
In [282]: s_multi = pd.Series(1, index=pd.MultiIndex.from_product([("a", "b"), (0,
↪ 1)]))

In [283]: build_table_schema(s_multi)
Out[283]:
{'fields': [{'name': 'level_0', 'type': 'string'},
  {'name': 'level_1', 'type': 'integer'},
  {'name': 'values', 'type': 'integer'}],
 'primaryKey': FrozenList(['level_0', 'level_1']),
 'pandas_version': '0.20.0'}
```

- The default naming roughly follows these rules:
  - For series, the `object.name` is used. If that's none, then the name is `values`
  - For `DataFrames`, the stringified version of the column name is used
  - For `Index` (not `MultiIndex`), `index.name` is used, with a fallback to `index` if that is None.
  - For `MultiIndex`, `mi.names` is used. If any level has no name, then `level_<i>` is used.

`read_json` also accepts `orient='table'` as an argument. This allows for the preservation of metadata such as dtypes and index names in a round-trippable manner.

```
In [284]: df = pd.DataFrame(
   .....:     {
   .....:         "foo": [1, 2, 3, 4],
   .....:         "bar": ["a", "b", "c", "d"],
   .....:         "baz": pd.date_range("2018-01-01", freq="d", periods=4),
   .....:         "qux": pd.Categorical(["a", "b", "c", "c"]),
   .....:     },
   .....:     index=pd.Index(range(4), name="idx"),
   .....: )
   .....:

In [285]: df
Out[285]:
     foo bar        baz qux
idx
0      1   a 2018-01-01   a
1      2   b 2018-01-02   b
2      3   c 2018-01-03   c
3      4   d 2018-01-04   c

In [286]: df.dtypes
Out[286]:
foo              int64
bar             object
baz     datetime64[ns]
qux           category
dtype: object
```

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```
In [287]: df.to_json("test.json", orient="table")

In [288]: new_df = pd.read_json("test.json", orient="table")

In [289]: new_df
Out[289]:
     foo bar        baz qux
idx
0      1   a 2018-01-01   a
1      2   b 2018-01-02   b
2      3   c 2018-01-03   c
3      4   d 2018-01-04   c

In [290]: new_df.dtypes
Out[290]:
foo              int64
bar             object
baz     datetime64[ns]
qux           category
dtype: object
```

Please note that the literal string 'index' as the name of an *Index* is not round-trippable, nor are any names beginning with `'level_'` within a *MultiIndex*. These are used by default in *DataFrame.to_json()* to indicate missing values and the subsequent read cannot distinguish the intent.

```
In [291]: df.index.name = "index"

In [292]: df.to_json("test.json", orient="table")

In [293]: new_df = pd.read_json("test.json", orient="table")

In [294]: print(new_df.index.name)
None
```

2.4.3 HTML

Reading HTML content

Warning: We **highly encourage** you to read the *HTML Table Parsing gotchas* below regarding the issues surrounding the BeautifulSoup4/html5lib/lxml parsers.

The top-level `read_html()` function can accept an HTML string/file/URL and will parse HTML tables into list of pandas `DataFrames`. Let's look at a few examples.

Note: `read_html` returns a `list` of `DataFrame` objects, even if there is only a single table contained in the HTML content.

Read a URL with no options:

```
In [295]: url = (
   .....:     "https://raw.githubusercontent.com/pandas-dev/pandas/master/"
   .....:     "pandas/tests/io/data/html/spam.html"
   .....: )
   .....:

In [296]: dfs = pd.read_html(url)

In [297]: dfs
Out[297]:
[                             Nutrient        Unit Value per 100.0g oz 1 NLEA␣
↪serving  56g  Unnamed: 4  Unnamed: 5
 0                            Proximates  Proximates       Proximates          ␣
↪Proximates  Proximates  Proximates
 1                                 Water           g            51.70          ␣
↪28.95         NaN         NaN
 2                                Energy        kcal              315          ␣
↪  176         NaN         NaN
 3                               Protein           g            13.40          ␣
↪ 7.50         NaN         NaN
 4                     Total lipid (fat)           g            26.60          ␣
↪14.90         NaN         NaN
 ..                                  ...         ...              ...          ␣
↪  ...         ...         ...
 32  Fatty acids, total monounsaturated           g          13.505           ␣
↪7.563         NaN         NaN
 33  Fatty acids, total polyunsaturated           g            2.019          ␣
↪1.131         NaN         NaN
 34                           Cholesterol          mg              71          ␣
↪   40         NaN         NaN
 35                                 Other       Other            Other          ␣
↪Other       Other       Other
 36                              Caffeine          mg                0          ␣
↪    0         NaN         NaN

 [37 rows x 6 columns]]
```

Read in the content of the "banklist.html" file and pass it to `read_html` as a string:

```
In [298]: with open(file_path, "r") as f:
   .....:     dfs = pd.read_html(f.read())
   .....:

In [299]: dfs
Out[299]:
[                                   Bank Name           City  ...       Closing Date ␣
↪     Updated Date
 0    Banks of Wisconsin d/b/a Bank of Kenosha       Kenosha  ...       May 31, 2013 ␣
↪     May 31, 2013
 1                      Central Arizona Bank    Scottsdale  ...       May 14, 2013 ␣
↪     May 20, 2013
 2                                 Sunrise Bank      Valdosta  ...       May 10, 2013 ␣
↪     May 21, 2013
 3                      Pisgah Community Bank     Asheville  ...       May 10, 2013 ␣
↪     May 14, 2013
 4                        Douglas County Bank  Douglasville  ...     April 26, 2013 ␣
↪     May 16, 2013
```

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```
..                                        ...           ...  ...                ... ␣
↪              ...
500                        Superior Bank, FSB      Hinsdale  ...      July 27, 2001 ␣
↪     June 5, 2012
501                       Malta National Bank         Malta  ...        May 3, 2001 ␣
↪November 18, 2002
502           First Alliance Bank & Trust Co.    Manchester  ...   February 2, 2001 ␣
↪February 18, 2003
503         National State Bank of Metropolis    Metropolis  ...  December 14, 2000 ␣
↪   March 17, 2005
504                          Bank of Honolulu      Honolulu  ...   October 13, 2000 ␣
↪   March 17, 2005

[505 rows x 7 columns]]
```

You can even pass in an instance of `StringIO` if you so desire:

```
In [300]: with open(file_path, "r") as f:
   .....:     sio = StringIO(f.read())
   .....:

In [301]: dfs = pd.read_html(sio)

In [302]: dfs
Out[302]:
[                                   Bank Name          City  ...       Closing Date ␣
↪     Updated Date
 0    Banks of Wisconsin d/b/a Bank of Kenosha       Kenosha  ...       May 31, 2013 ␣
↪     May 31, 2013
 1                        Central Arizona Bank    Scottsdale  ...       May 14, 2013 ␣
↪     May 20, 2013
 2                                Sunrise Bank      Valdosta  ...       May 10, 2013 ␣
↪     May 21, 2013
 3                       Pisgah Community Bank     Asheville  ...       May 10, 2013 ␣
↪     May 14, 2013
 4                         Douglas County Bank  Douglasville  ...     April 26, 2013 ␣
↪     May 16, 2013
 ..                                        ...           ...  ...                ... ␣
↪              ...
 500                        Superior Bank, FSB      Hinsdale  ...      July 27, 2001 ␣
↪     June 5, 2012
 501                       Malta National Bank         Malta  ...        May 3, 2001 ␣
↪November 18, 2002
 502           First Alliance Bank & Trust Co.    Manchester  ...   February 2, 2001 ␣
↪February 18, 2003
 503         National State Bank of Metropolis    Metropolis  ...  December 14, 2000 ␣
↪   March 17, 2005
 504                          Bank of Honolulu      Honolulu  ...   October 13, 2000 ␣
↪   March 17, 2005

[505 rows x 7 columns]]
```

Note: The following examples are not run by the IPython evaluator due to the fact that having so many network-accessing functions slows down the documentation build. If you spot an error or an example that doesn't run, please do not hesitate to report it over on pandas GitHub issues page.

Read a URL and match a table that contains specific text:

```
match = "Metcalf Bank"
df_list = pd.read_html(url, match=match)
```

Specify a header row (by default <th> or <td> elements located within a <thead> are used to form the column index, if multiple rows are contained within <thead> then a MultiIndex is created); if specified, the header row is taken from the data minus the parsed header elements (<th> elements).

```
dfs = pd.read_html(url, header=0)
```

Specify an index column:

```
dfs = pd.read_html(url, index_col=0)
```

Specify a number of rows to skip:

```
dfs = pd.read_html(url, skiprows=0)
```

Specify a number of rows to skip using a list (range works as well):

```
dfs = pd.read_html(url, skiprows=range(2))
```

Specify an HTML attribute:

```
dfs1 = pd.read_html(url, attrs={"id": "table"})
dfs2 = pd.read_html(url, attrs={"class": "sortable"})
print(np.array_equal(dfs1[0], dfs2[0]))  # Should be True
```

Specify values that should be converted to NaN:

```
dfs = pd.read_html(url, na_values=["No Acquirer"])
```

Specify whether to keep the default set of NaN values:

```
dfs = pd.read_html(url, keep_default_na=False)
```

Specify converters for columns. This is useful for numerical text data that has leading zeros. By default columns that are numerical are cast to numeric types and the leading zeros are lost. To avoid this, we can convert these columns to strings.

```
url_mcc = "https://en.wikipedia.org/wiki/Mobile_country_code"
dfs = pd.read_html(
    url_mcc,
    match="Telekom Albania",
    header=0,
    converters={"MNC": str},
)
```

Use some combination of the above:

```
dfs = pd.read_html(url, match="Metcalf Bank", index_col=0)
```

Read in pandas to_html output (with some loss of floating point precision):

```
df = pd.DataFrame(np.random.randn(2, 2))
s = df.to_html(float_format="{0:.40g}".format)
dfin = pd.read_html(s, index_col=0)
```

The `lxml` backend will raise an error on a failed parse if that is the only parser you provide. If you only have a single parser you can provide just a string, but it is considered good practice to pass a list with one string if, for example, the function expects a sequence of strings. You may use:

```
dfs = pd.read_html(url, "Metcalf Bank", index_col=0, flavor=["lxml"])
```

Or you could pass `flavor='lxml'` without a list:

```
dfs = pd.read_html(url, "Metcalf Bank", index_col=0, flavor="lxml")
```

However, if you have bs4 and html5lib installed and pass `None` or `['lxml', 'bs4']` then the parse will most likely succeed. Note that *as soon as a parse succeeds, the function will return*.

```
dfs = pd.read_html(url, "Metcalf Bank", index_col=0, flavor=["lxml", "bs4"])
```

Writing to HTML files

`DataFrame` objects have an instance method `to_html` which renders the contents of the `DataFrame` as an HTML table. The function arguments are as in the method `to_string` described above.

Note: Not all of the possible options for `DataFrame.to_html` are shown here for brevity's sake. See `to_html()` for the full set of options.

```
In [303]: df = pd.DataFrame(np.random.randn(2, 2))

In [304]: df
Out[304]:
          0         1
0 -0.184744  0.496971
1 -0.856240  1.857977

In [305]: print(df.to_html())  # raw html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

HTML:

The `columns` argument will limit the columns shown:

```
In [306]: print(df.to_html(columns=[0]))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
    </tr>
  </tbody>
</table>
```

HTML:

`float_format` takes a Python callable to control the precision of floating point values:

```
In [307]: print(df.to_html(float_format="{0:.10f}".format))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.1847438576</td>
      <td>0.4969711327</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.8562396763</td>
      <td>1.8579766508</td>
    </tr>
  </tbody>
</table>
```

HTML:

`bold_rows` will make the row labels bold by default, but you can turn that off:

```
In [308]: print(df.to_html(bold_rows=False))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
```

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```
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <td>0</td>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <td>1</td>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

The `classes` argument provides the ability to give the resulting HTML table CSS classes. Note that these classes are *appended* to the existing `'dataframe'` class.

```
In [309]: print(df.to_html(classes=["awesome_table_class", "even_more_awesome_class
↪"]))
<table border="1" class="dataframe awesome_table_class even_more_awesome_class">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

The `render_links` argument provides the ability to add hyperlinks to cells that contain URLs.

New in version 0.24.

```
In [310]: url_df = pd.DataFrame(
   .....:     {
   .....:         "name": ["Python", "pandas"],
   .....:         "url": ["https://www.python.org/", "https://pandas.pydata.org"],
   .....:     }
   ..... : )
   .....:

In [311]: print(url_df.to_html(render_links=True))
```

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```
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>name</th>
      <th>url</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>Python</td>
      <td><a href="https://www.python.org/" target="_blank">https://www.python.org/</
↪a></td>
    </tr>
    <tr>
      <th>1</th>
      <td>pandas</td>
      <td><a href="https://pandas.pydata.org" target="_blank">https://pandas.pydata.
↪org</a></td>
    </tr>
  </tbody>
</table>
```

HTML:

Finally, the `escape` argument allows you to control whether the "<", ">" and "&" characters escaped in the resulting HTML (by default it is `True`). So to get the HTML without escaped characters pass `escape=False`

```
In [312]: df = pd.DataFrame({"a": list("&<>"), "b": np.random.randn(3)})
```

Escaped:

```
In [313]: print(df.to_html())
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>a</th>
      <th>b</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>&amp;</td>
      <td>-0.474063</td>
    </tr>
    <tr>
      <th>1</th>
      <td>&lt;</td>
      <td>-0.230305</td>
    </tr>
    <tr>
      <th>2</th>
      <td>&gt;</td>
      <td>-0.400654</td>
```

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```
    </tr>
  </tbody>
</table>
```

Not escaped:

```
In [314]: print(df.to_html(escape=False))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>a</th>
      <th>b</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>&</td>
      <td>-0.474063</td>
    </tr>
    <tr>
      <th>1</th>
      <td><</td>
      <td>-0.230305</td>
    </tr>
    <tr>
      <th>2</th>
      <td>></td>
      <td>-0.400654</td>
    </tr>
  </tbody>
</table>
```

Note: Some browsers may not show a difference in the rendering of the previous two HTML tables.

HTML Table Parsing Gotchas

There are some versioning issues surrounding the libraries that are used to parse HTML tables in the top-level pandas io function `read_html`.

Issues with lxml

- Benefits
  - **lxml** is very fast.
  - **lxml** requires Cython to install correctly.
- Drawbacks
  - **lxml** does *not* make any guarantees about the results of its parse *unless* it is given **strictly valid markup**.
  - In light of the above, we have chosen to allow you, the user, to use the **lxml** backend, but **this backend will use html5lib** if **lxml** fails to parse

  - It is therefore *highly recommended* that you install both **BeautifulSoup4** and **html5lib**, so that you will still get a valid result (provided everything else is valid) even if **lxml** fails.

Issues with BeautifulSoup4 using lxml as a backend

- The above issues hold here as well since **BeautifulSoup4** is essentially just a wrapper around a parser backend.

Issues with BeautifulSoup4 using html5lib as a backend

- Benefits
  - **html5lib** is far more lenient than **lxml** and consequently deals with *real-life markup* in a much saner way rather than just, e.g., dropping an element without notifying you.
  - **html5lib** *generates valid HTML5 markup from invalid markup automatically*. This is extremely important for parsing HTML tables, since it guarantees a valid document. However, that does NOT mean that it is "correct", since the process of fixing markup does not have a single definition.
  - **html5lib** is pure Python and requires no additional build steps beyond its own installation.
- Drawbacks
  - The biggest drawback to using **html5lib** is that it is slow as molasses. However consider the fact that many tables on the web are not big enough for the parsing algorithm runtime to matter. It is more likely that the bottleneck will be in the process of reading the raw text from the URL over the web, i.e., IO (input-output). For very large tables, this might not be true.

2.4.4 Excel files

The *read_excel()* method can read Excel 2007+ (`.xlsx`) files using the `openpyxl` Python module. Excel 2003 (`.xls`) files can be read using `xlrd`. Binary Excel (`.xlsb`) files can be read using `pyxlsb`. The *to_excel()* instance method is used for saving a `DataFrame` to Excel. Generally the semantics are similar to working with *csv* data. See the *cookbook* for some advanced strategies.

Warning: The xlwt package for writing old-style `.xls` excel files is no longer maintained. The xlrd package is now only for reading old-style `.xls` files.

Before pandas 1.2.0, the default argument `engine=None` to *read_excel()* would result in using the `xlrd` engine in many cases, including new Excel 2007+ (`.xlsx`) files. If openpyxl is installed, many of these cases will now default to using the `openpyxl` engine. See the *read_excel()* documentation for more details.

Thus, it is strongly encouraged to install `openpyxl` to read Excel 2007+ (`.xlsx`) files. **Please do not report issues when using ``xlrd`` to read ``.xlsx`` files.** This is no longer supported, switch to using `openpyxl` instead.

Attempting to use the the `xlwt` engine will raise a `FutureWarning` unless the option `io.excel.xls.writer` is set to `"xlwt"`. While this option is now deprecated and will also raise a `FutureWarning`, it can be globally set and the warning suppressed. Users are recommended to write `.xlsx` files using the `openpyxl` engine instead.

Reading Excel files

In the most basic use-case, `read_excel` takes a path to an Excel file, and the `sheet_name` indicating which sheet to parse.

```
# Returns a DataFrame
pd.read_excel("path_to_file.xls", sheet_name="Sheet1")
```

`ExcelFile` class

To facilitate working with multiple sheets from the same file, the `ExcelFile` class can be used to wrap the file and can be passed into `read_excel` There will be a performance benefit for reading multiple sheets as the file is read into memory only once.

```
xlsx = pd.ExcelFile("path_to_file.xls")
df = pd.read_excel(xlsx, "Sheet1")
```

The `ExcelFile` class can also be used as a context manager.

```
with pd.ExcelFile("path_to_file.xls") as xls:
    df1 = pd.read_excel(xls, "Sheet1")
    df2 = pd.read_excel(xls, "Sheet2")
```

The `sheet_names` property will generate a list of the sheet names in the file.

The primary use-case for an `ExcelFile` is parsing multiple sheets with different parameters:

```
data = {}
# For when Sheet1's format differs from Sheet2
with pd.ExcelFile("path_to_file.xls") as xls:
    data["Sheet1"] = pd.read_excel(xls, "Sheet1", index_col=None, na_values=["NA"])
    data["Sheet2"] = pd.read_excel(xls, "Sheet2", index_col=1)
```

Note that if the same parsing parameters are used for all sheets, a list of sheet names can simply be passed to `read_excel` with no loss in performance.

```
# using the ExcelFile class
data = {}
with pd.ExcelFile("path_to_file.xls") as xls:
    data["Sheet1"] = pd.read_excel(xls, "Sheet1", index_col=None, na_values=["NA"])
    data["Sheet2"] = pd.read_excel(xls, "Sheet2", index_col=None, na_values=["NA"])

# equivalent using the read_excel function
data = pd.read_excel(
    "path_to_file.xls", ["Sheet1", "Sheet2"], index_col=None, na_values=["NA"]
)
```

`ExcelFile` can also be called with a `xlrd.book.Book` object as a parameter. This allows the user to control how the excel file is read. For example, sheets can be loaded on demand by calling `xlrd.open_workbook()` with `on_demand=True`.

```
import xlrd

xlrd_book = xlrd.open_workbook("path_to_file.xls", on_demand=True)
with pd.ExcelFile(xlrd_book) as xls:
```

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```
    df1 = pd.read_excel(xls, "Sheet1")
    df2 = pd.read_excel(xls, "Sheet2")
```

Specifying sheets

Note: The second argument is `sheet_name`, not to be confused with `ExcelFile.sheet_names`.

Note: An ExcelFile's attribute `sheet_names` provides access to a list of sheets.

- The arguments `sheet_name` allows specifying the sheet or sheets to read.
- The default value for `sheet_name` is 0, indicating to read the first sheet
- Pass a string to refer to the name of a particular sheet in the workbook.
- Pass an integer to refer to the index of a sheet. Indices follow Python convention, beginning at 0.
- Pass a list of either strings or integers, to return a dictionary of specified sheets.
- Pass a `None` to return a dictionary of all available sheets.

```
# Returns a DataFrame
pd.read_excel("path_to_file.xls", "Sheet1", index_col=None, na_values=["NA"])
```

Using the sheet index:

```
# Returns a DataFrame
pd.read_excel("path_to_file.xls", 0, index_col=None, na_values=["NA"])
```

Using all default values:

```
# Returns a DataFrame
pd.read_excel("path_to_file.xls")
```

Using None to get all sheets:

```
# Returns a dictionary of DataFrames
pd.read_excel("path_to_file.xls", sheet_name=None)
```

Using a list to get multiple sheets:

```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
pd.read_excel("path_to_file.xls", sheet_name=["Sheet1", 3])
```

`read_excel` can read more than one sheet, by setting `sheet_name` to either a list of sheet names, a list of sheet positions, or `None` to read all sheets. Sheets can be specified by sheet index or sheet name, using an integer or string, respectively.

Reading a `MultiIndex`

`read_excel` can read a `MultiIndex` index, by passing a list of columns to `index_col` and a `MultiIndex` column by passing a list of rows to `header`. If either the `index` or `columns` have serialized level names those will be read in as well by specifying the rows/columns that make up the levels.

For example, to read in a `MultiIndex` index without names:

```
In [315]: df = pd.DataFrame(
   .....:     {"a": [1, 2, 3, 4], "b": [5, 6, 7, 8]},
   .....:     index=pd.MultiIndex.from_product([["a", "b"], ["c", "d"]]),
   .....: )
   .....:

In [316]: df.to_excel("path_to_file.xlsx")

In [317]: df = pd.read_excel("path_to_file.xlsx", index_col=[0, 1])

In [318]: df
Out[318]:
      a  b
a c   1  5
  d   2  6
b c   3  7
  d   4  8
```

If the index has level names, they will parsed as well, using the same parameters.

```
In [319]: df.index = df.index.set_names(["lvl1", "lvl2"])

In [320]: df.to_excel("path_to_file.xlsx")

In [321]: df = pd.read_excel("path_to_file.xlsx", index_col=[0, 1])

In [322]: df
Out[322]:
            a  b
lvl1 lvl2
a    c      1  5
     d      2  6
b    c      3  7
     d      4  8
```

If the source file has both `MultiIndex` index and columns, lists specifying each should be passed to `index_col` and `header`:

```
In [323]: df.columns = pd.MultiIndex.from_product([["a"], ["b", "d"]], names=["c1",
↪"c2"])

In [324]: df.to_excel("path_to_file.xlsx")

In [325]: df = pd.read_excel("path_to_file.xlsx", index_col=[0, 1], header=[0, 1])

In [326]: df
Out[326]:
c1         a
c2         b  d
lvl1 lvl2
```

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```
a    c    1  5
     d    2  6
b    c    3  7
     d    4  8
```

Parsing specific columns

It is often the case that users will insert columns to do temporary computations in Excel and you may not want to read in those columns. `read_excel` takes a `usecols` keyword to allow you to specify a subset of columns to parse.

Changed in version 1.0.0.

Passing in an integer for `usecols` will no longer work. Please pass in a list of ints from 0 to `usecols` inclusive instead.

You can specify a comma-delimited set of Excel columns and ranges as a string:

```
pd.read_excel("path_to_file.xls", "Sheet1", usecols="A,C:E")
```

If `usecols` is a list of integers, then it is assumed to be the file column indices to be parsed.

```
pd.read_excel("path_to_file.xls", "Sheet1", usecols=[0, 2, 3])
```

Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`.

New in version 0.24.

If `usecols` is a list of strings, it is assumed that each string corresponds to a column name provided either by the user in `names` or inferred from the document header row(s). Those strings define which columns will be parsed:

```
pd.read_excel("path_to_file.xls", "Sheet1", usecols=["foo", "bar"])
```

Element order is ignored, so `usecols=['baz', 'joe']` is the same as `['joe', 'baz']`.

New in version 0.24.

If `usecols` is callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to `True`.

```
pd.read_excel("path_to_file.xls", "Sheet1", usecols=lambda x: x.isalpha())
```

Parsing dates

Datetime-like values are normally automatically converted to the appropriate dtype when reading the excel file. But if you have a column of strings that *look* like dates (but are not actually formatted as dates in excel), you can use the `parse_dates` keyword to parse those strings to datetimes:

```
pd.read_excel("path_to_file.xls", "Sheet1", parse_dates=["date_strings"])
```

Cell converters

It is possible to transform the contents of Excel cells via the `converters` option. For instance, to convert a column to boolean:

```
pd.read_excel("path_to_file.xls", "Sheet1", converters={"MyBools": bool})
```

This options handles missing values and treats exceptions in the converters as missing data. Transformations are applied cell by cell rather than to the column as a whole, so the array dtype is not guaranteed. For instance, a column of integers with missing values cannot be transformed to an array with integer dtype, because NaN is strictly a float. You can manually mask missing data to recover integer dtype:

```
def cfun(x):
    return int(x) if x else -1


pd.read_excel("path_to_file.xls", "Sheet1", converters={"MyInts": cfun})
```

Dtype specifications

As an alternative to converters, the type for an entire column can be specified using the `dtype` keyword, which takes a dictionary mapping column names to types. To interpret data with no type inference, use the type `str` or `object`.

```
pd.read_excel("path_to_file.xls", dtype={"MyInts": "int64", "MyText": str})
```

Writing Excel files

Writing Excel files to disk

To write a `DataFrame` object to a sheet of an Excel file, you can use the `to_excel` instance method. The arguments are largely the same as `to_csv` described above, the first argument being the name of the excel file, and the optional second argument the name of the sheet to which the `DataFrame` should be written. For example:

```
df.to_excel("path_to_file.xlsx", sheet_name="Sheet1")
```

Files with a `.xls` extension will be written using `xlwt` and those with a `.xlsx` extension will be written using `xlsxwriter` (if available) or `openpyxl`.

The `DataFrame` will be written in a way that tries to mimic the REPL output. The `index_label` will be placed in the second row instead of the first. You can place it in the first row by setting the `merge_cells` option in `to_excel()` to `False`:

```
df.to_excel("path_to_file.xlsx", index_label="label", merge_cells=False)
```

In order to write separate `DataFrames` to separate sheets in a single Excel file, one can pass an `ExcelWriter`.

```
with pd.ExcelWriter("path_to_file.xlsx") as writer:
    df1.to_excel(writer, sheet_name="Sheet1")
    df2.to_excel(writer, sheet_name="Sheet2")
```

Note: Wringing a little more performance out of `read_excel` Internally, Excel stores all numeric data as floats. Because this can produce unexpected behavior when reading in data, pandas defaults to trying to convert integers to

floats if it doesn't lose information (`1.0 --> 1`). You can pass `convert_float=False` to disable this behavior, which may give a slight performance improvement.

Writing Excel files to memory

pandas supports writing Excel files to buffer-like objects such as `StringIO` or `BytesIO` using `ExcelWriter`.

```
from io import BytesIO

bio = BytesIO()

# By setting the 'engine' in the ExcelWriter constructor.
writer = pd.ExcelWriter(bio, engine="xlsxwriter")
df.to_excel(writer, sheet_name="Sheet1")

# Save the workbook
writer.save()

# Seek to the beginning and read to copy the workbook to a variable in memory
bio.seek(0)
workbook = bio.read()
```

Note: `engine` is optional but recommended. Setting the engine determines the version of workbook produced. Setting `engine='xlrd'` will produce an Excel 2003-format workbook (xls). Using either `'openpyxl'` or `'xlsxwriter'` will produce an Excel 2007-format workbook (xlsx). If omitted, an Excel 2007-formatted workbook is produced.

Excel writer engines

Deprecated since version 1.2.0: As the xlwt package is no longer maintained, the `xlwt` engine will be removed from a future version of pandas. This is the only engine in pandas that supports writing to `.xls` files.

pandas chooses an Excel writer via two methods:

1. the `engine` keyword argument
2. the filename extension (via the default specified in config options)

By default, pandas uses the XlsxWriter for `.xlsx`, openpyxl for `.xlsm`, and xlwt for `.xls` files. If you have multiple engines installed, you can set the default engine through *setting the config options* `io.excel.xlsx.writer` and `io.excel.xls.writer`. pandas will fall back on openpyxl for `.xlsx` files if Xlsxwriter is not available.

To specify which writer you want to use, you can pass an engine keyword argument to `to_excel` and to `ExcelWriter`. The built-in engines are:

- `openpyxl`: version 2.4 or higher is required
- `xlsxwriter`
- `xlwt`

```
# By setting the 'engine' in the DataFrame 'to_excel()' methods.
df.to_excel("path_to_file.xlsx", sheet_name="Sheet1", engine="xlsxwriter")
```

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```
# By setting the 'engine' in the ExcelWriter constructor.
writer = pd.ExcelWriter("path_to_file.xlsx", engine="xlsxwriter")

# Or via pandas configuration.
from pandas import options  # noqa: E402

options.io.excel.xlsx.writer = "xlsxwriter"

df.to_excel("path_to_file.xlsx", sheet_name="Sheet1")
```

Style and formatting

The look and feel of Excel worksheets created from pandas can be modified using the following parameters on the `DataFrame`'s `to_excel` method.

- `float_format` : Format string for floating point numbers (default `None`).
- `freeze_panes` : A tuple of two integers representing the bottommost row and rightmost column to freeze. Each of these parameters is one-based, so (1, 1) will freeze the first row and first column (default `None`).

Using the Xlsxwriter engine provides many options for controlling the format of an Excel worksheet created with the `to_excel` method. Excellent examples can be found in the Xlsxwriter documentation here: https://xlsxwriter.readthedocs.io/working_with_pandas.html

2.4.5 OpenDocument Spreadsheets

New in version 0.25.

The *`read_excel()`* method can also read OpenDocument spreadsheets using the `odfpy` module. The semantics and features for reading OpenDocument spreadsheets match what can be done for *Excel files* using `engine='odf'`.

```
# Returns a DataFrame
pd.read_excel("path_to_file.ods", engine="odf")
```

Note: Currently pandas only supports *reading* OpenDocument spreadsheets. Writing is not implemented.

2.4.6 Binary Excel (.xlsb) files

New in version 1.0.0.

The *`read_excel()`* method can also read binary Excel files using the `pyxlsb` module. The semantics and features for reading binary Excel files mostly match what can be done for *Excel files* using `engine='pyxlsb'`. `pyxlsb` does not recognize datetime types in files and will return floats instead.

```
# Returns a DataFrame
pd.read_excel("path_to_file.xlsb", engine="pyxlsb")
```

Note: Currently pandas only supports *reading* binary Excel files. Writing is not implemented.

2.4.7 Clipboard

A handy way to grab data is to use the `read_clipboard()` method, which takes the contents of the clipboard buffer and passes them to the `read_csv` method. For instance, you can copy the following text to the clipboard (CTRL-C on many operating systems):

```
  A B C
x 1 4 p
y 2 5 q
z 3 6 r
```

And then import the data directly to a `DataFrame` by calling:

```
>>> clipdf = pd.read_clipboard()
>>> clipdf
  A B C
x 1 4 p
y 2 5 q
z 3 6 r
```

The `to_clipboard` method can be used to write the contents of a `DataFrame` to the clipboard. Following which you can paste the clipboard contents into other applications (CTRL-V on many operating systems). Here we illustrate writing a `DataFrame` into clipboard and reading it back.

```
>>> df = pd.DataFrame(
...     {"A": [1, 2, 3], "B": [4, 5, 6], "C": ["p", "q", "r"]}, index=["x", "y", "z"]
... )

>>> df
  A B C
x 1 4 p
y 2 5 q
z 3 6 r
>>> df.to_clipboard()
>>> pd.read_clipboard()
  A B C
x 1 4 p
y 2 5 q
z 3 6 r
```

We can see that we got the same content back, which we had earlier written to the clipboard.

Note: You may need to install xclip or xsel (with PyQt5, PyQt4 or qtpy) on Linux to use these methods.

2.4.8 Pickling

All pandas objects are equipped with `to_pickle` methods which use Python's `cPickle` module to save data structures to disk using the pickle format.

```
In [327]: df
Out[327]:
c1          a
c2          b  d
lvl1 lvl2
```

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```
a     c     1  5
      d     2  6
b     c     3  7
      d     4  8

In [328]: df.to_pickle("foo.pkl")
```

The `read_pickle` function in the `pandas` namespace can be used to load any pickled pandas object (or any other pickled object) from file:

```
In [329]: pd.read_pickle("foo.pkl")
Out[329]:
c1          a
c2          b  d
lvl1 lvl2
a    c      1  5
     d      2  6
b    c      3  7
     d      4  8
```

Warning: Loading pickled data received from untrusted sources can be unsafe.

See: https://docs.python.org/3/library/pickle.html

Warning: *`read_pickle()`* is only guaranteed backwards compatible back to pandas version 0.20.3

Compressed pickle files

`read_pickle()`, *`DataFrame.to_pickle()`* and *`Series.to_pickle()`* can read and write compressed pickle files. The compression types of `gzip`, `bz2`, `xz` are supported for reading and writing. The `zip` file format only supports reading and must contain only one data file to be read.

The compression type can be an explicit parameter or be inferred from the file extension. If 'infer', then use `gzip`, `bz2`, `zip`, or `xz` if filename ends in `'.gz'`, `'.bz2'`, `'.zip'`, or `'.xz'`, respectively.

The compression parameter can also be a `dict` in order to pass options to the compression protocol. It must have a `'method'` key set to the name of the compression protocol, which must be one of {`'zip'`, `'gzip'`, `'bz2'`}. All other key-value pairs are passed to the underlying compression library.

```
In [330]: df = pd.DataFrame(
   .....:     {
   .....:         "A": np.random.randn(1000),
   .....:         "B": "foo",
   .....:         "C": pd.date_range("20130101", periods=1000, freq="s"),
   .....:     }
   .....: )
   .....:

In [331]: df
Out[331]:
          A    B                   C
0  -0.288267  foo 2013-01-01 00:00:00
```

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```
1   -0.084905  foo 2013-01-01 00:00:01
2    0.004772  foo 2013-01-01 00:00:02
3    1.382989  foo 2013-01-01 00:00:03
4    0.343635  foo 2013-01-01 00:00:04
..        ...  ...                 ...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39

[1000 rows x 3 columns]
```

Using an explicit compression type:

```
In [332]: df.to_pickle("data.pkl.compress", compression="gzip")

In [333]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")

In [334]: rt
Out[334]:
            A    B                   C
0   -0.288267  foo 2013-01-01 00:00:00
1   -0.084905  foo 2013-01-01 00:00:01
2    0.004772  foo 2013-01-01 00:00:02
3    1.382989  foo 2013-01-01 00:00:03
4    0.343635  foo 2013-01-01 00:00:04
..        ...  ...                 ...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39

[1000 rows x 3 columns]
```

Inferring compression type from the extension:

```
In [335]: df.to_pickle("data.pkl.xz", compression="infer")

In [336]: rt = pd.read_pickle("data.pkl.xz", compression="infer")

In [337]: rt
Out[337]:
            A    B                   C
0   -0.288267  foo 2013-01-01 00:00:00
1   -0.084905  foo 2013-01-01 00:00:01
2    0.004772  foo 2013-01-01 00:00:02
3    1.382989  foo 2013-01-01 00:00:03
4    0.343635  foo 2013-01-01 00:00:04
..        ...  ...                 ...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39
```

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```
[1000 rows x 3 columns]
```

The default is to 'infer':

```
In [338]: df.to_pickle("data.pkl.gz")

In [339]: rt = pd.read_pickle("data.pkl.gz")

In [340]: rt
Out[340]:
            A    B                   C
0   -0.288267  foo 2013-01-01 00:00:00
1   -0.084905  foo 2013-01-01 00:00:01
2    0.004772  foo 2013-01-01 00:00:02
3    1.382989  foo 2013-01-01 00:00:03
4    0.343635  foo 2013-01-01 00:00:04
..        ...  ...                 ...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39

[1000 rows x 3 columns]

In [341]: df["A"].to_pickle("s1.pkl.bz2")

In [342]: rt = pd.read_pickle("s1.pkl.bz2")

In [343]: rt
Out[343]:
0     -0.288267
1     -0.084905
2      0.004772
3      1.382989
4      0.343635
         ...
995   -0.220893
996    0.492996
997   -0.461625
998    1.361779
999   -1.197988
Name: A, Length: 1000, dtype: float64
```

Passing options to the compression protocol in order to speed up compression:

```
In [344]: df.to_pickle("data.pkl.gz", compression={"method": "gzip", "compresslevel":␣
↪1})
```

2.4.9 msgpack

pandas support for `msgpack` has been removed in version 1.0.0. It is recommended to use pyarrow for on-the-wire transmission of pandas objects.

Example pyarrow usage:

```
import pandas as pd
import pyarrow as pa

df = pd.DataFrame({"A": [1, 2, 3]})

context = pa.default_serialization_context()
df_bytestring = context.serialize(df).to_buffer().to_pybytes()
```

For documentation on pyarrow, see here.

2.4.10 HDF5 (PyTables)

`HDFStore` is a dict-like object which reads and writes pandas using the high performance HDF5 format using the excellent PyTables library. See the *cookbook* for some advanced strategies

Warning: pandas uses PyTables for reading and writing HDF5 files, which allows serializing object-dtype data with pickle. Loading pickled data received from untrusted sources can be unsafe.

See: https://docs.python.org/3/library/pickle.html for more.

```
In [345]: store = pd.HDFStore("store.h5")

In [346]: print(store)
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

Objects can be written to the file just like adding key-value pairs to a dict:

```
In [347]: index = pd.date_range("1/1/2000", periods=8)

In [348]: s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])

In [349]: df = pd.DataFrame(np.random.randn(8, 3), index=index, columns=["A", "B", "C
↪"])

# store.put('s', s) is an equivalent method
In [350]: store["s"] = s

In [351]: store["df"] = df

In [352]: store
Out[352]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

In a current or later Python session, you can retrieve stored objects:

```
# store.get('df') is an equivalent method
In [353]: store["df"]
Out[353]:
                   A         B         C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288

# dotted (attribute) access provides get as well
In [354]: store.df
Out[354]:
                   A         B         C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
```

Deletion of the object specified by the key:

```
# store.remove('df') is an equivalent method
In [355]: del store["df"]

In [356]: store
Out[356]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

Closing a Store and using a context manager:

```
In [357]: store.close()

In [358]: store
Out[358]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

In [359]: store.is_open
Out[359]: False

# Working with, and automatically closing the store using a context manager
In [360]: with pd.HDFStore("store.h5") as store:
   .....:     store.keys()
   .....:
```

Read/write API

`HDFStore` supports a top-level API using `read_hdf` for reading and `to_hdf` for writing, similar to how `read_csv` and `to_csv` work.

```
In [361]: df_tl = pd.DataFrame({"A": list(range(5)), "B": list(range(5))})

In [362]: df_tl.to_hdf("store_tl.h5", "table", append=True)

In [363]: pd.read_hdf("store_tl.h5", "table", where=["index>2"])
Out[363]:
   A  B
3  3  3
4  4  4
```

HDFStore will by default not drop rows that are all missing. This behavior can be changed by setting `dropna=True`.

```
In [364]: df_with_missing = pd.DataFrame(
   .....:     {
   .....:         "col1": [0, np.nan, 2],
   .....:         "col2": [1, np.nan, np.nan],
   .....:     }
   .....: )
   .....:

In [365]: df_with_missing
Out[365]:
   col1  col2
0   0.0   1.0
1   NaN   NaN
2   2.0   NaN

In [366]: df_with_missing.to_hdf("file.h5", "df_with_missing", format="table", mode="w
↪")

In [367]: pd.read_hdf("file.h5", "df_with_missing")
Out[367]:
   col1  col2
0   0.0   1.0
1   NaN   NaN
2   2.0   NaN

In [368]: df_with_missing.to_hdf(
   .....:     "file.h5", "df_with_missing", format="table", mode="w", dropna=True
   .....: )
   .....:

In [369]: pd.read_hdf("file.h5", "df_with_missing")
Out[369]:
   col1  col2
0   0.0   1.0
2   2.0   NaN
```

Fixed format

The examples above show storing using `put`, which write the HDF5 to `PyTables` in a fixed array format, called the `fixed` format. These types of stores are **not** appendable once written (though you can simply remove them and rewrite). Nor are they **queryable**; they must be retrieved in their entirety. They also do not support dataframes with non-unique column names. The `fixed` format stores offer very fast writing and slightly faster reading than `table` stores. This format is specified by default when using `put` or `to_hdf` or by `format='fixed'` or `format='f'`.

Warning: A `fixed` format will raise a `TypeError` if you try to retrieve using a `where`:

```
>>> pd.DataFrame(np.random.randn(10, 2)).to_hdf("test_fixed.h5", "df")
>>> pd.read_hdf("test_fixed.h5", "df", where="index>5")
TypeError: cannot pass a where specification when reading a fixed format.
           this store must be selected in its entirety
```

Table format

`HDFStore` supports another `PyTables` format on disk, the `table` format. Conceptually a `table` is shaped very much like a DataFrame, with rows and columns. A `table` may be appended to in the same or other sessions. In addition, delete and query type operations are supported. This format is specified by `format='table'` or `format='t'` to `append` or `put` or `to_hdf`.

This format can be set as an option as well `pd.set_option('io.hdf.default_format','table')` to enable `put/append/to_hdf` to by default store in the `table` format.

```
In [370]: store = pd.HDFStore("store.h5")

In [371]: df1 = df[0:4]

In [372]: df2 = df[4:]

# append data (creates a table automatically)
In [373]: store.append("df", df1)

In [374]: store.append("df", df2)

In [375]: store
Out[375]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# select the entire object
In [376]: store.select("df")
Out[376]:
                   A         B         C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288

# the type of stored data
```

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```
In [377]: store.root.df._v_attrs.pandas_type
Out[377]: 'frame_table'
```

Note: You can also create a `table` by passing `format='table'` or `format='t'` to a `put` operation.

Hierarchical keys

Keys to a store can be specified as a string. These can be in a hierarchical path-name like format (e.g. `foo/bar/bah`), which will generate a hierarchy of sub-stores (or `Groups` in PyTables parlance). Keys can be specified without the leading '/' and are **always** absolute (e.g. 'foo' refers to '/foo'). Removal operations can remove everything in the sub-store and **below**, so be *careful*.

```
In [378]: store.put("foo/bar/bah", df)

In [379]: store.append("food/orange", df)

In [380]: store.append("food/apple", df)

In [381]: store
Out[381]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# a list of keys are returned
In [382]: store.keys()
Out[382]: ['/df', '/food/apple', '/food/orange', '/foo/bar/bah']

# remove all nodes under this level
In [383]: store.remove("food")

In [384]: store
Out[384]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

You can walk through the group hierarchy using the `walk` method which will yield a tuple for each group key along with the relative keys of its contents.

New in version 0.24.0.

```
In [385]: for (path, subgroups, subkeys) in store.walk():
   .....:     for subgroup in subgroups:
   .....:         print("GROUP: {}/{}".format(path, subgroup))
   .....:     for subkey in subkeys:
   .....:         key = "/".join([path, subkey])
   .....:         print("KEY: {}".format(key))
   .....:         print(store.get(key))
   .....:
GROUP: /foo
KEY: /df
                   A         B         C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
```

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```
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
GROUP: /foo/bar
KEY: /foo/bar/bah
                   A         B         C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
```

Warning: Hierarchical keys cannot be retrieved as dotted (attribute) access as described above for items stored under the root node.

```
In [8]: store.foo.bar.bah
AttributeError: 'HDFStore' object has no attribute 'foo'

# you can directly access the actual PyTables node but using the root node
In [9]: store.root.foo.bar.bah
Out[9]:
/foo/bar/bah (Group) ''
  children := ['block0_items' (Array), 'block0_values' (Array), 'axis0' (Array),
↪'axis1' (Array)]
```

Instead, use explicit string based keys:

```
In [386]: store["foo/bar/bah"]
Out[386]:
                   A         B         C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
```

Storing types

Storing mixed types in a table

Storing mixed-dtype data is supported. Strings are stored as a fixed-width using the maximum size of the appended column. Subsequent attempts at appending longer strings will raise a `ValueError`.

Passing `min_itemsize={`values`: size}` as a parameter to append will set a larger minimum for the string columns. Storing `floats, strings, ints, bools, datetime64` are currently supported. For string columns, passing `nan_rep = 'nan'` to append will change the default nan representation on disk (which converts to/from `np.nan`), this defaults to `nan`.

```
In [387]: df_mixed = pd.DataFrame(
   .....:     {
   .....:         "A": np.random.randn(8),
   .....:         "B": np.random.randn(8),
   .....:         "C": np.array(np.random.randn(8), dtype="float32"),
   .....:         "string": "string",
   .....:         "int": 1,
   .....:         "bool": True,
   .....:         "datetime64": pd.Timestamp("20010102"),
   .....:     },
   .....:     index=list(range(8)),
   .....: )
   .....:

In [388]: df_mixed.loc[df_mixed.index[3:5], ["A", "B", "string", "datetime64"]] = np.
↪nan

In [389]: store.append("df_mixed", df_mixed, min_itemsize={"values": 50})

In [390]: df_mixed1 = store.select("df_mixed")

In [391]: df_mixed1
Out[391]:
          A         B         C  string  int  bool datetime64
0 -0.116008  0.743946 -0.398501  string    1  True 2001-01-02
1  0.592375 -0.533097 -0.677311  string    1  True 2001-01-02
2  0.476481 -0.140850 -0.874991  string    1  True 2001-01-02
3       NaN       NaN -1.167564     NaN    1  True        NaT
4       NaN       NaN -0.593353     NaN    1  True        NaT
5  0.852727  0.463819  0.146262  string    1  True 2001-01-02
6 -1.177365  0.793644 -0.131959  string    1  True 2001-01-02
7  1.236988  0.221252  0.089012  string    1  True 2001-01-02

In [392]: df_mixed1.dtypes.value_counts()
Out[392]:
float64           2
int64             1
float32           1
bool              1
datetime64[ns]    1
object            1
dtype: int64

# we have provided a minimum string column size
In [393]: store.root.df_mixed.table
```

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```
Out[393]:
/df_mixed/table (Table(8,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(2,), dflt=0.0, pos=1),
  "values_block_1": Float32Col(shape=(1,), dflt=0.0, pos=2),
  "values_block_2": Int64Col(shape=(1,), dflt=0, pos=3),
  "values_block_3": Int64Col(shape=(1,), dflt=0, pos=4),
  "values_block_4": BoolCol(shape=(1,), dflt=False, pos=5),
  "values_block_5": StringCol(itemsize=50, shape=(1,), dflt=b'', pos=6)}
  byteorder := 'little'
  chunkshape := (689,)
  autoindex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

Storing MultiIndex DataFrames

Storing MultiIndex `DataFrames` as tables is very similar to storing/selecting from homogeneous index `DataFrames`.

```
In [394]: index = pd.MultiIndex(
   .....:     levels=[["foo", "bar", "baz", "qux"], ["one", "two", "three"]],
   .....:     codes=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3], [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
   .....:     names=["foo", "bar"],
   .....: )
   .....:

In [395]: df_mi = pd.DataFrame(np.random.randn(10, 3), index=index, columns=["A", "B",
 ↪ "C"])

In [396]: df_mi
Out[396]:
                  A         B         C
foo bar
foo one    0.667450  0.169405 -1.358046
    two   -0.105563  0.492195  0.076693
    three  0.213685 -0.285283 -1.210529
bar one   -1.408386  0.941577 -0.342447
    two    0.222031  0.052607  2.093214
baz two    1.064908  1.778161 -0.913867
    three -0.030004 -0.399846 -1.234765
qux one    0.081323 -0.268494  0.168016
    two   -0.898283 -0.218499  1.408028
    three -1.267828 -0.689263  0.520995

In [397]: store.append("df_mi", df_mi)

In [398]: store.select("df_mi")
Out[398]:
                  A         B         C
foo bar
foo one    0.667450  0.169405 -1.358046
    two   -0.105563  0.492195  0.076693
    three  0.213685 -0.285283 -1.210529
```

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```
bar one   -1.408386  0.941577 -0.342447
    two    0.222031  0.052607  2.093214
baz two    1.064908  1.778161 -0.913867
    three -0.030004 -0.399846 -1.234765
qux one    0.081323 -0.268494  0.168016
    two   -0.898283 -0.218499  1.408028
    three -1.267828 -0.689263  0.520995

# the levels are automatically included as data columns
In [399]: store.select("df_mi", "foo=bar")
Out[399]:
                A         B         C
foo bar
bar one -1.408386  0.941577 -0.342447
    two  0.222031  0.052607  2.093214
```

Note: The `index` keyword is reserved and cannot be use as a level name.

Querying

Querying a table

`select` and `delete` operations have an optional criterion that can be specified to select/delete only a subset of the data. This allows one to have a very large on-disk table and retrieve only a portion of the data.

A query is specified using the `Term` class under the hood, as a boolean expression.

- `index` and `columns` are supported indexers of `DataFrames`.
- if `data_columns` are specified, these can be used as additional indexers.
- level name in a MultiIndex, with default name `level_0`, `level_1`, … if not provided.

Valid comparison operators are:

`=, ==, !=, >, >=, <, <=`

Valid boolean expressions are combined with:

- `|` : or
- `&` : and
- `(` and `)` : for grouping

These rules are similar to how boolean expressions are used in pandas for indexing.

Note:

- = will be automatically expanded to the comparison operator ==
- ~ is the not operator, but can only be used in very limited circumstances
- If a list/tuple of expressions is passed they will be combined via `&`

The following are valid expressions:

- 'index >= date'
- "columns = ['A', 'D']"
- "columns in ['A', 'D']"
- 'columns = A'
- 'columns == A'
- "~(columns = ['A', 'B'])"
- 'index > df.index[3] & string = "bar"'
- '(index > df.index[3] & index <= df.index[6]) | string = "bar"'
- "ts >= Timestamp('2012-02-01')"
- "major_axis>=20130101"

The indexers are on the left-hand side of the sub-expression:

columns, major_axis, ts

The right-hand side of the sub-expression (after a comparison operator) can be:

- functions that will be evaluated, e.g. Timestamp('2012-02-01')
- strings, e.g. "bar"
- date-like, e.g. 20130101, or "20130101"
- lists, e.g. "['A', 'B']"
- variables that are defined in the local names space, e.g. date

---

Note: Passing a string to a query by interpolating it into the query expression is not recommended. Simply assign the string of interest to a variable and use that variable in an expression. For example, do this

```
string = "HolyMoly'"
store.select("df", "index == string")
```

instead of this

```
string = "HolyMoly'"
store.select('df', f'index == {string}')
```

The latter will **not** work and will raise a SyntaxError.Note that there's a single quote followed by a double quote in the string variable.

If you *must* interpolate, use the '%r' format specifier

```
store.select("df", "index == %r" % string)
```

which will quote string.

Here are some examples:

```
In [400]: dfq = pd.DataFrame(
   .....:     np.random.randn(10, 4),
   .....:     columns=list("ABCD"),
   .....:     index=pd.date_range("20130101", periods=10),
   .....: )
```

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```
   .....:

In [401]: store.append("dfq", dfq, format="table", data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```
In [402]: store.select("dfq", "index>pd.Timestamp('20130104') & columns=['A', 'B']")
Out[402]:
                   A         B
2013-01-05 -1.083889  0.811865
2013-01-06 -0.402227  1.618922
2013-01-07  0.948196  0.183573
2013-01-08 -1.043530 -0.708145
2013-01-09  0.813949  1.508891
2013-01-10  1.176488 -1.246093
```

Use inline column reference.

```
In [403]: store.select("dfq", where="A>0 or C>0")
Out[403]:
                   A         B         C         D
2013-01-01  0.620028  0.159416 -0.263043 -0.639244
2013-01-04 -0.536722  1.005707  0.296917  0.139796
2013-01-05 -1.083889  0.811865  1.648435 -0.164377
2013-01-07  0.948196  0.183573  0.145277  0.308146
2013-01-08 -1.043530 -0.708145  1.430905 -0.850136
2013-01-09  0.813949  1.508891 -1.556154  0.187597
2013-01-10  1.176488 -1.246093 -0.002726 -0.444249
```

The `columns` keyword can be supplied to select a list of columns to be returned, this is equivalent to passing a `'columns=list_of_columns_to_filter'`:

```
In [404]: store.select("df", "columns=['A', 'B']")
Out[404]:
                   A         B
2000-01-01  1.334065  0.521036
2000-01-02 -1.613932  1.088104
2000-01-03 -0.585314 -0.275038
2000-01-04  0.632369 -1.249657
2000-01-05  1.060617 -0.143682
2000-01-06  3.050329  1.317933
2000-01-07 -0.539452 -0.771133
2000-01-08  0.649464 -1.736427
```

`start` and `stop` parameters can be specified to limit the total search space. These are in terms of the total number of rows in a table.

Note: `select` will raise a `ValueError` if the query expression has an unknown variable reference. Usually this means that you are trying to select on a column that is **not** a data_column.

`select` will raise a `SyntaxError` if the query expression is not valid.

Query timedelta64[ns]

You can store and query using the `timedelta64[ns]` type. Terms can be specified in the format: `<float>(<unit>)`, where float may be signed (and fractional), and unit can be `D,s,ms,us,ns` for the timedelta. Here's an example:

```
In [405]: from datetime import timedelta

In [406]: dftd = pd.DataFrame(
   .....:     {
   .....:         "A": pd.Timestamp("20130101"),
   .....:         "B": [
   .....:             pd.Timestamp("20130101") + timedelta(days=i, seconds=10)
   .....:             for i in range(10)
   .....:         ],
   .....:     }
   .....: )
   .....:

In [407]: dftd["C"] = dftd["A"] - dftd["B"]

In [408]: dftd
Out[408]:
           A                   B                   C
0 2013-01-01 2013-01-01 00:00:10  -1 days +23:59:50
1 2013-01-01 2013-01-02 00:00:10  -2 days +23:59:50
2 2013-01-01 2013-01-03 00:00:10  -3 days +23:59:50
3 2013-01-01 2013-01-04 00:00:10  -4 days +23:59:50
4 2013-01-01 2013-01-05 00:00:10  -5 days +23:59:50
5 2013-01-01 2013-01-06 00:00:10  -6 days +23:59:50
6 2013-01-01 2013-01-07 00:00:10  -7 days +23:59:50
7 2013-01-01 2013-01-08 00:00:10  -8 days +23:59:50
8 2013-01-01 2013-01-09 00:00:10  -9 days +23:59:50
9 2013-01-01 2013-01-10 00:00:10 -10 days +23:59:50

In [409]: store.append("dftd", dftd, data_columns=True)

In [410]: store.select("dftd", "C<'-3.5D'")
Out[410]:
           A                   B                   C
4 2013-01-01 2013-01-05 00:00:10  -5 days +23:59:50
5 2013-01-01 2013-01-06 00:00:10  -6 days +23:59:50
6 2013-01-01 2013-01-07 00:00:10  -7 days +23:59:50
7 2013-01-01 2013-01-08 00:00:10  -8 days +23:59:50
8 2013-01-01 2013-01-09 00:00:10  -9 days +23:59:50
9 2013-01-01 2013-01-10 00:00:10 -10 days +23:59:50
```

Query MultiIndex

Selecting from a `MultiIndex` can be achieved by using the name of the level.

```
In [411]: df_mi.index.names
Out[411]: FrozenList(['foo', 'bar'])

In [412]: store.select("df_mi", "foo=baz and bar=two")
Out[412]:
                A         B         C
foo bar
baz two  1.064908  1.778161 -0.913867
```

If the `MultiIndex` levels names are `None`, the levels are automatically made available via the `level_n` keyword with `n` the level of the `MultiIndex` you want to select from.

```
In [413]: index = pd.MultiIndex(
   .....:     levels=[["foo", "bar", "baz", "qux"], ["one", "two", "three"]],
   .....:     codes=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3], [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
   .....: )
   .....:

In [414]: df_mi_2 = pd.DataFrame(np.random.randn(10, 3), index=index, columns=["A", "B
↪", "C"])

In [415]: df_mi_2
Out[415]:
                  A         B         C
foo one    0.856838  1.491776  0.001283
    two    0.701816 -1.097917  0.102588
    three  0.661740  0.443531  0.559313
bar one   -0.459055 -1.222598 -0.455304
    two   -0.781163  0.826204 -0.530057
baz two    0.296135  1.366810  1.073372
    three -0.994957  0.755314  2.119746
qux one   -2.628174 -0.089460 -0.133636
    two    0.337920 -0.634027  0.421107
    three  0.604303  1.053434  1.109090

In [416]: store.append("df_mi_2", df_mi_2)

# the levels are automatically included as data columns with keyword level_n
In [417]: store.select("df_mi_2", "level_0=foo and level_1=two")
Out[417]:
                A         B         C
foo two  0.701816 -1.097917  0.102588
```

Indexing

You can create/modify an index for a table with `create_table_index` after data is already in the table (after and `append/put` operation). Creating a table index is **highly** encouraged. This will speed your queries a great deal when you use a `select` with the indexed dimension as the `where`.

Note: Indexes are automagically created on the indexables and any data columns you specify. This behavior can be turned off by passing `index=False` to `append`.

```
# we have automagically already created an index (in the first section)
In [418]: i = store.root.df.table.cols.index.index

In [419]: i.optlevel, i.kind
Out[419]: (6, 'medium')

# change an index by passing new parameters
In [420]: store.create_table_index("df", optlevel=9, kind="full")

In [421]: i = store.root.df.table.cols.index.index

In [422]: i.optlevel, i.kind
Out[422]: (9, 'full')
```

Oftentimes when appending large amounts of data to a store, it is useful to turn off index creation for each append, then recreate at the end.

```
In [423]: df_1 = pd.DataFrame(np.random.randn(10, 2), columns=list("AB"))

In [424]: df_2 = pd.DataFrame(np.random.randn(10, 2), columns=list("AB"))

In [425]: st = pd.HDFStore("appends.h5", mode="w")

In [426]: st.append("df", df_1, data_columns=["B"], index=False)

In [427]: st.append("df", df_2, data_columns=["B"], index=False)

In [428]: st.get_storer("df").table
Out[428]:
/df/table (Table(20,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
  "B": Float64Col(shape=(), dflt=0.0, pos=2)}
  byteorder := 'little'
  chunkshape := (2730,)
```

Then create the index when finished appending.

```
In [429]: st.create_table_index("df", columns=["B"], optlevel=9, kind="full")

In [430]: st.get_storer("df").table
Out[430]:
/df/table (Table(20,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
```

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```
  "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
  "B": Float64Col(shape=(), dflt=0.0, pos=2)}
  byteorder := 'little'
  chunkshape := (2730,)
  autoindex := True
  colindexes := {
    "B": Index(9, full, shuffle, zlib(1)).is_csi=True}

In [431]: st.close()
```

See here for how to create a completely-sorted-index (CSI) on an existing store.

Query via data columns

You can designate (and index) certain columns that you want to be able to perform queries (other than the `indexable` columns, which you can always query). For instance say you want to perform this common operation, on-disk, and return just the frame that matches this query. You can specify `data_columns = True` to force all columns to be `data_columns`.

```
In [432]: df_dc = df.copy()

In [433]: df_dc["string"] = "foo"

In [434]: df_dc.loc[df_dc.index[4:6], "string"] = np.nan

In [435]: df_dc.loc[df_dc.index[7:9], "string"] = "bar"

In [436]: df_dc["string2"] = "cool"

In [437]: df_dc.loc[df_dc.index[1:3], ["B", "C"]] = 1.0

In [438]: df_dc
Out[438]:
                   A         B         C string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool
2000-01-04  0.632369 -1.249657  0.975593    foo    cool
2000-01-05  1.060617 -0.143682  0.218423    NaN    cool
2000-01-06  3.050329  1.317933 -0.963725    NaN    cool
2000-01-07 -0.539452 -0.771133  0.023751    foo    cool
2000-01-08  0.649464 -1.736427  0.197288    bar    cool

# on-disk operations
In [439]: store.append("df_dc", df_dc, data_columns=["B", "C", "string", "string2"])

In [440]: store.select("df_dc", where="B > 0")
Out[440]:
                   A         B         C string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool
2000-01-06  3.050329  1.317933 -0.963725    NaN    cool

# getting creative
```

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```
In [441]: store.select("df_dc", "B > 0 & C > 0 & string == foo")
Out[441]:
                   A         B         C string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool

# this is in-memory version of this type of selection
In [442]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == "foo")]
Out[442]:
                   A         B         C string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool

# we have automagically created this index and the B/C/string/string2
# columns are stored separately as ``PyTables`` columns
In [443]: store.root.df_dc.table
Out[443]:
/df_dc/table (Table(8,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
  "B": Float64Col(shape=(), dflt=0.0, pos=2),
  "C": Float64Col(shape=(), dflt=0.0, pos=3),
  "string": StringCol(itemsize=3, shape=(), dflt=b'', pos=4),
  "string2": StringCol(itemsize=4, shape=(), dflt=b'', pos=5)}
  byteorder := 'little'
  chunkshape := (1680,)
  autoindex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "B": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "C": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string2": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

There is some performance degradation by making lots of columns into `data columns`, so it is up to the user to designate these. In addition, you cannot change data columns (nor indexables) after the first append/put operation (Of course you can simply read in the data and create a new table!).

Iterator

You can pass `iterator=True` or `chunksize=number_in_a_chunk` to `select` and `select_as_multiple` to return an iterator on the results. The default is 50,000 rows returned in a chunk.

```
In [444]: for df in store.select("df", chunksize=3):
   .....:     print(df)
   .....:
                   A         B         C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
                   A         B         C
2000-01-04  0.632369 -1.249657  0.975593
```

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```
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
                   A         B         C
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
```

Note: You can also use the iterator with `read_hdf` which will open, then automatically close the store when finished iterating.

```
for df in pd.read_hdf("store.h5", "df", chunksize=3):
    print(df)
```

Note, that the chunksize keyword applies to the **source** rows. So if you are doing a query, then the chunksize will subdivide the total rows in the table and the query applied, returning an iterator on potentially unequal sized chunks.

Here is a recipe for generating a query and using it to create equal sized return chunks.

```
In [445]: dfeq = pd.DataFrame({"number": np.arange(1, 11)})

In [446]: dfeq
Out[446]:
   number
0       1
1       2
2       3
3       4
4       5
5       6
6       7
7       8
8       9
9      10

In [447]: store.append("dfeq", dfeq, data_columns=["number"])

In [448]: def chunks(l, n):
   .....:     return [l[i: i + n] for i in range(0, len(l), n)]
   .....:

In [449]: evens = [2, 4, 6, 8, 10]

In [450]: coordinates = store.select_as_coordinates("dfeq", "number=evens")

In [451]: for c in chunks(coordinates, 2):
   .....:     print(store.select("dfeq", where=c))
   .....:
   number
1       2
3       4
   number
5       6
7       8
   number
9      10
```

Advanced queries

Select a single column

To retrieve a single indexable or data column, use the method `select_column`. This will, for example, enable you to get the index very quickly. These return a `Series` of the result, indexed by the row number. These do not currently accept the `where` selector.

```
In [452]: store.select_column("df_dc", "index")
Out[452]:
0   2000-01-01
1   2000-01-02
2   2000-01-03
3   2000-01-04
4   2000-01-05
5   2000-01-06
6   2000-01-07
7   2000-01-08
Name: index, dtype: datetime64[ns]

In [453]: store.select_column("df_dc", "string")
Out[453]:
0    foo
1    foo
2    foo
3    foo
4    NaN
5    NaN
6    foo
7    bar
Name: string, dtype: object
```

Selecting coordinates

Sometimes you want to get the coordinates (a.k.a the index locations) of your query. This returns an `Int64Index` of the resulting locations. These coordinates can also be passed to subsequent `where` operations.

```
In [454]: df_coord = pd.DataFrame(
   .....:     np.random.randn(1000, 2), index=pd.date_range("20000101", periods=1000)
   .....: )
   .....:

In [455]: store.append("df_coord", df_coord)

In [456]: c = store.select_as_coordinates("df_coord", "index > 20020101")

In [457]: c
Out[457]:
Int64Index([732, 733, 734, 735, 736, 737, 738, 739, 740, 741,
            ...
            990, 991, 992, 993, 994, 995, 996, 997, 998, 999],
           dtype='int64', length=268)

In [458]: store.select("df_coord", where=c)
Out[458]:
```

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```
                   0         1
2002-01-02 -0.165548  0.646989
2002-01-03  0.782753 -0.123409
2002-01-04 -0.391932 -0.740915
2002-01-05  1.211070 -0.668715
2002-01-06  0.341987 -0.685867
...              ...       ...
2002-09-22  1.788110 -0.405908
2002-09-23 -0.801912  0.768460
2002-09-24  0.466284 -0.457411
2002-09-25 -0.364060  0.785367
2002-09-26 -1.463093  1.187315

[268 rows x 2 columns]
```

Selecting using a where mask

Sometime your query can involve creating a list of rows to select. Usually this `mask` would be a resulting `index` from an indexing operation. This example selects the months of a datetimeindex which are 5.

```
In [459]: df_mask = pd.DataFrame(
   .....:     np.random.randn(1000, 2), index=pd.date_range("20000101", periods=1000)
   .....: )
   .....:

In [460]: store.append("df_mask", df_mask)

In [461]: c = store.select_column("df_mask", "index")

In [462]: where = c[pd.DatetimeIndex(c).month == 5].index

In [463]: store.select("df_mask", where=where)
Out[463]:
                   0         1
2000-05-01  1.735883 -2.615261
2000-05-02  0.422173  2.425154
2000-05-03  0.632453 -0.165640
2000-05-04 -1.017207 -0.005696
2000-05-05  0.299606  0.070606
...              ...       ...
2002-05-27  0.234503  1.199126
2002-05-28 -3.021833 -1.016828
2002-05-29  0.522794  0.063465
2002-05-30 -1.653736  0.031709
2002-05-31 -0.968402 -0.393583

[93 rows x 2 columns]
```

Storer object

If you want to inspect the stored object, retrieve via `get_storer`. You could use this programmatically to say get the number of rows in an object.

```
In [464]: store.get_storer("df_dc").nrows
Out[464]: 8
```

Multiple table queries

The methods `append_to_multiple` and `select_as_multiple` can perform appending/selecting from multiple tables at once. The idea is to have one table (call it the selector table) that you index most/all of the columns, and perform your queries. The other table(s) are data tables with an index matching the selector table's index. You can then perform a very fast query on the selector table, yet get lots of data back. This method is similar to having a very wide table, but enables more efficient queries.

The `append_to_multiple` method splits a given single DataFrame into multiple tables according to `d`, a dictionary that maps the table names to a list of 'columns' you want in that table. If `None` is used in place of a list, that table will have the remaining unspecified columns of the given DataFrame. The argument `selector` defines which table is the selector table (which you can make queries from). The argument `dropna` will drop rows from the input `DataFrame` to ensure tables are synchronized. This means that if a row for one of the tables being written to is entirely `np.NaN`, that row will be dropped from all tables.

If `dropna` is False, **THE USER IS RESPONSIBLE FOR SYNCHRONIZING THE TABLES**. Remember that entirely `np.Nan` rows are not written to the HDFStore, so if you choose to call `dropna=False`, some tables may have more rows than others, and therefore `select_as_multiple` may not work or it may return unexpected results.

```
In [465]: df_mt = pd.DataFrame(
   .....:     np.random.randn(8, 6),
   .....:     index=pd.date_range("1/1/2000", periods=8),
   .....:     columns=["A", "B", "C", "D", "E", "F"],
   .....: )
   .....:

In [466]: df_mt["foo"] = "bar"

In [467]: df_mt.loc[df_mt.index[1], ("A", "B")] = np.nan

# you can also create the tables individually
In [468]: store.append_to_multiple(
   .....:     {"df1_mt": ["A", "B"], "df2_mt": None}, df_mt, selector="df1_mt"
   .....: )
   .....:

In [469]: store
Out[469]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# individual tables were created
In [470]: store.select("df1_mt")
Out[470]:
                   A         B
2000-01-01  1.251079 -0.362628
```

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```
2000-01-02       NaN       NaN
2000-01-03  0.719421 -0.448886
2000-01-04  1.140998 -0.877922
2000-01-05  1.043605  1.798494
2000-01-06 -0.467812 -0.027965
2000-01-07  0.150568  0.754820
2000-01-08 -0.596306 -0.910022

In [471]: store.select("df2_mt")
Out[471]:
                   C         D         E         F  foo
2000-01-01  1.602451 -0.221229  0.712403  0.465927  bar
2000-01-02 -0.525571  0.851566 -0.681308 -0.549386  bar
2000-01-03 -0.044171  1.396628  1.041242 -1.588171  bar
2000-01-04  0.463351 -0.861042 -2.192841 -1.025263  bar
2000-01-05 -1.954845 -1.712882 -0.204377 -1.608953  bar
2000-01-06  1.601542 -0.417884 -2.757922 -0.307713  bar
2000-01-07 -1.935461  1.007668  0.079529 -1.459471  bar
2000-01-08 -1.057072 -0.864360 -1.124870  1.732966  bar

# as a multiple
In [472]: store.select_as_multiple(
   .....:     ["df1_mt", "df2_mt"],
   .....:     where=["A>0", "B>0"],
   .....:     selector="df1_mt",
   .....: )
   .....:
Out[472]:
                   A         B         C         D         E         F  foo
2000-01-05  1.043605  1.798494 -1.954845 -1.712882 -0.204377 -1.608953  bar
2000-01-07  0.150568  0.754820 -1.935461  1.007668  0.079529 -1.459471  bar
```

Delete from a table

You can delete from a table selectively by specifying a `where`. In deleting rows, it is important to understand the `PyTables` deletes rows by erasing the rows, then **moving** the following data. Thus deleting can potentially be a very expensive operation depending on the orientation of your data. To get optimal performance, it's worthwhile to have the dimension you are deleting be the first of the `indexables`.

Data is ordered (on the disk) in terms of the `indexables`. Here's a simple use case. You store panel-type data, with dates in the `major_axis` and ids in the `minor_axis`. The data is then interleaved like this:

- **date_1**
  - id_1
  - id_2
  - .
  - id_n
- **date_2**
  - id_1
  - .
  - id_n

It should be clear that a delete operation on the `major_axis` will be fairly quick, as one chunk is removed, then the following data moved. On the other hand a delete operation on the `minor_axis` will be very expensive. In this case it would almost certainly be faster to rewrite the table using a `where` that selects all but the missing data.

Warning: Please note that HDF5 **DOES NOT RECLAIM SPACE** in the h5 files automatically. Thus, repeatedly deleting (or removing nodes) and adding again, **WILL TEND TO INCREASE THE FILE SIZE**.

To *repack and clean* the file, use *ptrepack*.

Notes & caveats

Compression

`PyTables` allows the stored data to be compressed. This applies to all kinds of stores, not just tables. Two parameters are used to control compression: `complevel` and `complib`.

- `complevel` specifies if and how hard data is to be compressed. `complevel=0` and `complevel=None` disables compression and `0<complevel<10` enables compression.
- `complib` specifies which compression library to use. If nothing is specified the default library `zlib` is used. A compression library usually optimizes for either good compression rates or speed and the results will depend on the type of data. Which type of compression to choose depends on your specific needs and data. The list of supported compression libraries:
  - zlib: The default compression library. A classic in terms of compression, achieves good compression rates but is somewhat slow.
  - lzo: Fast compression and decompression.
  - bzip2: Good compression rates.
  - blosc: Fast compression and decompression.

    Support for alternative blosc compressors:

    * blosc:blosclz This is the default compressor for `blosc`
    * blosc:lz4: A compact, very popular and fast compressor.
    * blosc:lz4hc: A tweaked version of LZ4, produces better compression ratios at the expense of speed.
    * blosc:snappy: A popular compressor used in many places.
    * blosc:zlib: A classic; somewhat slower than the previous ones, but achieving better compression ratios.
    * blosc:zstd: An extremely well balanced codec; it provides the best compression ratios among the others above, and at reasonably fast speed.

  If `complib` is defined as something other than the listed libraries a `ValueError` exception is issued.

Note: If the library specified with the `complib` option is missing on your platform, compression defaults to `zlib` without further ado.

Enable compression for all objects within the file:

```
store_compressed = pd.HDFStore(
    "store_compressed.h5", complevel=9, complib="blosc:blosclz"
)
```

Or on-the-fly compression (this only applies to tables) in stores where compression is not enabled:

```
store.append("df", df, complib="zlib", complevel=5)
```

ptrepack

`PyTables` offers better write performance when tables are compressed after they are written, as opposed to turning on compression at the very beginning. You can use the supplied `PyTables` utility `ptrepack`. In addition, `ptrepack` can change compression levels after the fact.

```
ptrepack --chunkshape=auto --propindexes --complevel=9 --complib=blosc in.h5 out.h5
```

Furthermore `ptrepack in.h5 out.h5` will *repack* the file to allow you to reuse previously deleted space. Alternatively, one can simply remove the file and write again, or use the `copy` method.

Caveats

Warning: `HDFStore` is **not-threadsafe for writing**. The underlying `PyTables` only supports concurrent reads (via threading or processes). If you need reading and writing *at the same time*, you need to serialize these operations in a single thread in a single process. You will corrupt your data otherwise. See the (GH2397) for more information.

- If you use locks to manage write access between multiple processes, you may want to use `fsync()` before releasing write locks. For convenience you can use `store.flush(fsync=True)` to do this for you.
- Once a `table` is created columns (DataFrame) are fixed; only exactly the same columns can be appended
- Be aware that timezones (e.g., `pytz.timezone('US/Eastern')`) are not necessarily equal across timezone versions. So if data is localized to a specific timezone in the HDFStore using one version of a timezone library and that data is updated with another version, the data will be converted to UTC since these timezones are not considered equal. Either use the same version of timezone library or use `tz_convert` with the updated timezone definition.

Warning: `PyTables` will show a `NaturalNameWarning` if a column name cannot be used as an attribute selector. *Natural* identifiers contain only letters, numbers, and underscores, and may not begin with a number. Other identifiers cannot be used in a `where` clause and are generally a bad idea.

DataTypes

`HDFStore` will map an object dtype to the `PyTables` underlying dtype. This means the following types are known to work:

Type	Represents missing values
floating : `float64, float32, float16`	`np.nan`
integer : `int64, int32, int8, uint64,uint32, uint8`	
boolean	
`datetime64[ns]`	`NaT`
`timedelta64[ns]`	`NaT`
categorical : see the section below	
object : `strings`	`np.nan`

`unicode` columns are not supported, and **WILL FAIL**.

Categorical data

You can write data that contains `category` dtypes to a `HDFStore`. Queries work the same as if it was an object array. However, the `category` dtyped data is stored in a more efficient manner.

```
In [473]: dfcat = pd.DataFrame(
   .....:     {"A": pd.Series(list("aabbcdba")).astype("category"), "B": np.random.
↪randn(8)}
   .....: )
   .....:

In [474]: dfcat
Out[474]:
   A         B
0  a  0.477849
1  a  0.283128
2  b -2.045700
3  b -0.338206
4  c -0.423113
5  d  2.314361
6  b -0.033100
7  a -0.965461

In [475]: dfcat.dtypes
Out[475]:
A    category
B     float64
dtype: object

In [476]: cstore = pd.HDFStore("cats.h5", mode="w")

In [477]: cstore.append("dfcat", dfcat, format="table", data_columns=["A"])

In [478]: result = cstore.select("dfcat", where="A in ['b', 'c']")

In [479]: result
Out[479]:
   A         B
```

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```
2  b -2.045700
3  b -0.338206
4  c -0.423113
6  b -0.033100

In [480]: result.dtypes
Out[480]:
A    category
B     float64
dtype: object
```

String columns

min_itemsize

The underlying implementation of `HDFStore` uses a fixed column width (itemsize) for string columns. A string column itemsize is calculated as the maximum of the length of data (for that column) that is passed to the `HDFStore`, **in the first append**. Subsequent appends, may introduce a string for a column **larger** than the column can hold, an Exception will be raised (otherwise you could have a silent truncation of these columns, leading to loss of information). In the future we may relax this and allow a user-specified truncation to occur.

Pass `min_itemsize` on the first table creation to a-priori specify the minimum length of a particular string column. `min_itemsize` can be an integer, or a dict mapping a column name to an integer. You can pass `values` as a key to allow all *indexables* or *data_columns* to have this min_itemsize.

Passing a `min_itemsize` dict will cause all passed columns to be created as *data_columns* automatically.

Note: If you are not passing any `data_columns`, then the `min_itemsize` will be the maximum of the length of any string passed

---

```
In [481]: dfs = pd.DataFrame({"A": "foo", "B": "bar"}, index=list(range(5)))

In [482]: dfs
Out[482]:
     A    B
0  foo  bar
1  foo  bar
2  foo  bar
3  foo  bar
4  foo  bar

# A and B have a size of 30
In [483]: store.append("dfs", dfs, min_itemsize=30)

In [484]: store.get_storer("dfs").table
Out[484]:
/dfs/table (Table(5,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": StringCol(itemsize=30, shape=(2,), dflt=b'', pos=1)}
  byteorder := 'little'
  chunkshape := (963,)
  autoindex := True
```

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```
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}

# A is created as a data_column with a size of 30
# B is size is calculated
In [485]: store.append("dfs2", dfs, min_itemsize={"A": 30})

In [486]: store.get_storer("dfs2").table
Out[486]:
/dfs2/table (Table(5,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": StringCol(itemsize=3, shape=(1,), dflt=b'', pos=1),
  "A": StringCol(itemsize=30, shape=(), dflt=b'', pos=2)}
  byteorder := 'little'
  chunkshape := (1598,)
  autoindex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "A": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

nan_rep

String columns will serialize a `np.nan` (a missing value) with the `nan_rep` string representation. This defaults to the string value `nan`. You could inadvertently turn an actual `nan` value into a missing value.

```
In [487]: dfss = pd.DataFrame({"A": ["foo", "bar", "nan"]})

In [488]: dfss
Out[488]:
     A
0  foo
1  bar
2  nan

In [489]: store.append("dfss", dfss)

In [490]: store.select("dfss")
Out[490]:
     A
0  foo
1  bar
2  NaN

# here you need to specify a different nan rep
In [491]: store.append("dfss2", dfss, nan_rep="_nan_")

In [492]: store.select("dfss2")
Out[492]:
     A
0  foo
1  bar
2  nan
```

External compatibility

`HDFStore` writes `table` format objects in specific formats suitable for producing loss-less round trips to pandas objects. For external compatibility, `HDFStore` can read native `PyTables` format tables.

It is possible to write an `HDFStore` object that can easily be imported into `R` using the `rhdf5` library (Package website). Create a table format store like this:

```
In [493]: df_for_r = pd.DataFrame(
   .....:     {
   .....:         "first": np.random.rand(100),
   .....:         "second": np.random.rand(100),
   .....:         "class": np.random.randint(0, 2, (100,)),
   .....:     },
   .....:     index=range(100),
   .....: )
   .....:

In [494]: df_for_r.head()
Out[494]:
      first    second  class
0  0.864919  0.852910      0
1  0.030579  0.412962      1
2  0.015226  0.978410      0
3  0.498512  0.686761      0
4  0.232163  0.328185      1

In [495]: store_export = pd.HDFStore("export.h5")

In [496]: store_export.append("df_for_r", df_for_r, data_columns=df_dc.columns)

In [497]: store_export
Out[497]:
<class 'pandas.io.pytables.HDFStore'>
File path: export.h5
```

In R this file can be read into a `data.frame` object using the `rhdf5` library. The following example function reads the corresponding column names and data values from the values and assembles them into a `data.frame`:

```
# Load values and column names for all datasets from corresponding nodes and
# insert them into one data.frame object.

library(rhdf5)

loadhdf5data <- function(h5File) {

listing <- h5ls(h5File)
# Find all data nodes, values are stored in *_values and corresponding column
# titles in *_items
data_nodes <- grep("_values", listing$name)
name_nodes <- grep("_items", listing$name)
data_paths = paste(listing$group[data_nodes], listing$name[data_nodes], sep = "/")
name_paths = paste(listing$group[name_nodes], listing$name[name_nodes], sep = "/")
columns = list()
for (idx in seq(data_paths)) {
  # NOTE: matrices returned by h5read have to be transposed to obtain
  # required Fortran order!
  data <- data.frame(t(h5read(h5File, data_paths[idx])))
```

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```
  names <- t(h5read(h5File, name_paths[idx]))
  entry <- data.frame(data)
  colnames(entry) <- names
  columns <- append(columns, entry)
}

data <- data.frame(columns)

return(data)
}
```

Now you can import the `DataFrame` into R:

```
> data = loadhdf5data("transfer.hdf5")
> head(data)
         first    second class
1 0.4170220047 0.3266449     0
2 0.7203244934 0.5270581     0
3 0.0001143748 0.8859421     1
4 0.3023325726 0.3572698     1
5 0.1467558908 0.9085352     1
6 0.0923385948 0.6233601     1
```

Note: The R function lists the entire HDF5 file's contents and assembles the `data.frame` object from all matching nodes, so use this only as a starting point if you have stored multiple `DataFrame` objects to a single HDF5 file.

Performance

- `tables` format come with a writing performance penalty as compared to `fixed` stores. The benefit is the ability to append/delete and query (potentially very large amounts of data). Write times are generally longer as compared with regular stores. Query times can be quite fast, especially on an indexed axis.
- You can pass `chunksize=<int>` to `append`, specifying the write chunksize (default is 50000). This will significantly lower your memory usage on writing.
- You can pass `expectedrows=<int>` to the first `append`, to set the TOTAL number of rows that `PyTables` will expect. This will optimize read/write performance.
- Duplicate rows can be written to tables, but are filtered out in selection (with the last items being selected; thus a table is unique on major, minor pairs)
- A `PerformanceWarning` will be raised if you are attempting to store types that will be pickled by PyTables (rather than stored as endemic types). See Here for more information and some solutions.

2.4.11 Feather

Feather provides binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy.

Feather is designed to faithfully serialize and de-serialize DataFrames, supporting all of the pandas dtypes, including extension dtypes such as categorical and datetime with tz.

Several caveats:

- The format will NOT write an `Index`, or `MultiIndex` for the `DataFrame` and will raise an error if a non-default one is provided. You can `.reset_index()` to store the index or `.reset_index(drop=True)` to ignore it.
- Duplicate column names and non-string columns names are not supported
- Actual Python objects in object dtype columns are not supported. These will raise a helpful error message on an attempt at serialization.

See the Full Documentation.

```
In [498]: df = pd.DataFrame(
   .....:     {
   .....:         "a": list("abc"),
   .....:         "b": list(range(1, 4)),
   .....:         "c": np.arange(3, 6).astype("u1"),
   .....:         "d": np.arange(4.0, 7.0, dtype="float64"),
   .....:         "e": [True, False, True],
   .....:         "f": pd.Categorical(list("abc")),
   .....:         "g": pd.date_range("20130101", periods=3),
   .....:         "h": pd.date_range("20130101", periods=3, tz="US/Eastern"),
   .....:         "i": pd.date_range("20130101", periods=3, freq="ns"),
   .....:     }
   .....: )
   .....:

In [499]: df
Out[499]:
   a  b  c    d      e  f          g                         h                 ␣
↪      i
0  a  1  3  4.0   True  a 2013-01-01 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00.
↪000000000
1  b  2  4  5.0  False  b 2013-01-02 2013-01-02 00:00:00-05:00 2013-01-01 00:00:00.
↪000000001
2  c  3  5  6.0   True  c 2013-01-03 2013-01-03 00:00:00-05:00 2013-01-01 00:00:00.
↪000000002

In [500]: df.dtypes
Out[500]:
a                         object
b                          int64
c                          uint8
d                        float64
e                           bool
f                       category
g                 datetime64[ns]
h    datetime64[ns, US/Eastern]
i                 datetime64[ns]
dtype: object
```

Write to a feather file.

```
In [501]: df.to_feather("example.feather")
```

Read from a feather file.

```
In [502]: result = pd.read_feather("example.feather")

In [503]: result
Out[503]:
   a  b  c    d      e  f          g                          h                          i
0  a  1  3  4.0   True  a 2013-01-01 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00.000000000
1  b  2  4  5.0  False  b 2013-01-02 2013-01-02 00:00:00-05:00 2013-01-01 00:00:00.000000001
2  c  3  5  6.0   True  c 2013-01-03 2013-01-03 00:00:00-05:00 2013-01-01 00:00:00.000000002

# we preserve dtypes
In [504]: result.dtypes
Out[504]:
a                          object
b                           int64
c                           uint8
d                         float64
e                            bool
f                        category
g                  datetime64[ns]
h    datetime64[ns, US/Eastern]
i                  datetime64[ns]
dtype: object
```

2.4.12 Parquet

Apache Parquet provides a partitioned binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy. Parquet can use a variety of compression techniques to shrink the file size as much as possible while still maintaining good read performance.

Parquet is designed to faithfully serialize and de-serialize `DataFrame` s, supporting all of the pandas dtypes, including extension dtypes such as datetime with tz.

Several caveats.

- Duplicate column names and non-string columns names are not supported.
- The `pyarrow` engine always writes the index to the output, but `fastparquet` only writes non-default indexes. This extra column can cause problems for non-pandas consumers that are not expecting it. You can force including or omitting indexes with the `index` argument, regardless of the underlying engine.
- Index level names, if specified, must be strings.
- In the `pyarrow` engine, categorical dtypes for non-string types can be serialized to parquet, but will de-serialize as their primitive dtype.
- The `pyarrow` engine preserves the `ordered` flag of categorical dtypes with string types. `fastparquet` does not preserve the `ordered` flag.

- Non supported types include `Interval` and actual Python object types. These will raise a helpful error message on an attempt at serialization. `Period` type is supported with pyarrow >= 0.16.0.
- The `pyarrow` engine preserves extension data types such as the nullable integer and string data type (requiring pyarrow >= 0.16.0, and requiring the extension type to implement the needed protocols, see the *extension types documentation*).

You can specify an `engine` to direct the serialization. This can be one of `pyarrow`, or `fastparquet`, or `auto`. If the engine is NOT specified, then the `pd.options.io.parquet.engine` option is checked; if this is also `auto`, then `pyarrow` is tried, and falling back to `fastparquet`.

See the documentation for pyarrow and fastparquet.

Note: These engines are very similar and should read/write nearly identical parquet format files. Currently `pyarrow` does not support timedelta data, `fastparquet>=0.1.4` supports timezone aware datetimes. These libraries differ by having different underlying dependencies (`fastparquet` by using `numba`, while `pyarrow` uses a c-library).

```
In [505]: df = pd.DataFrame(
   .....:     {
   .....:         "a": list("abc"),
   .....:         "b": list(range(1, 4)),
   .....:         "c": np.arange(3, 6).astype("u1"),
   .....:         "d": np.arange(4.0, 7.0, dtype="float64"),
   .....:         "e": [True, False, True],
   .....:         "f": pd.date_range("20130101", periods=3),
   .....:         "g": pd.date_range("20130101", periods=3, tz="US/Eastern"),
   .....:         "h": pd.Categorical(list("abc")),
   .....:         "i": pd.Categorical(list("abc"), ordered=True),
   .....:     }
   .....: )
   .....:

In [506]: df
Out[506]:
   a  b  c    d      e          f                          g  h  i
0  a  1  3  4.0   True 2013-01-01 2013-01-01 00:00:00-05:00  a  a
1  b  2  4  5.0  False 2013-01-02 2013-01-02 00:00:00-05:00  b  b
2  c  3  5  6.0   True 2013-01-03 2013-01-03 00:00:00-05:00  c  c

In [507]: df.dtypes
Out[507]:
a                         object
b                          int64
c                          uint8
d                        float64
e                           bool
f                  datetime64[ns]
g    datetime64[ns, US/Eastern]
h                       category
i                       category
dtype: object
```

Write to a parquet file.

```
In [508]: df.to_parquet("example_pa.parquet", engine="pyarrow")

In [509]: df.to_parquet("example_fp.parquet", engine="fastparquet")
```

Read from a parquet file.

```
In [510]: result = pd.read_parquet("example_fp.parquet", engine="fastparquet")

In [511]: result = pd.read_parquet("example_pa.parquet", engine="pyarrow")

In [512]: result.dtypes
Out[512]:
a                         object
b                          int64
c                          uint8
d                        float64
e                           bool
f                 datetime64[ns]
g    datetime64[ns, US/Eastern]
h                       category
i                       category
dtype: object
```

Read only certain columns of a parquet file.

```
In [513]: result = pd.read_parquet(
   .....:     "example_fp.parquet",
   .....:     engine="fastparquet",
   .....:     columns=["a", "b"],
   .....: )
   .....:

In [514]: result = pd.read_parquet(
   .....:     "example_pa.parquet",
   .....:     engine="pyarrow",
   .....:     columns=["a", "b"],
   .....: )
   .....:

In [515]: result.dtypes
Out[515]:
a    object
b     int64
dtype: object
```

Handling indexes

Serializing a `DataFrame` to parquet may include the implicit index as one or more columns in the output file. Thus, this code:

```
In [516]: df = pd.DataFrame({"a": [1, 2], "b": [3, 4]})

In [517]: df.to_parquet("test.parquet", engine="pyarrow")
```

creates a parquet file with *three* columns if you use `pyarrow` for serialization: `a`, `b`, and `__index_level_0__`. If you're using `fastparquet`, the index may or may not be written to the file.

This unexpected extra column causes some databases like Amazon Redshift to reject the file, because that column doesn't exist in the target table.

If you want to omit a dataframe's indexes when writing, pass `index=False` to *`to_parquet()`*:

```
In [518]: df.to_parquet("test.parquet", index=False)
```

This creates a parquet file with just the two expected columns, `a` and `b`. If your `DataFrame` has a custom index, you won't get it back when you load this file into a `DataFrame`.

Passing `index=True` will *always* write the index, even if that's not the underlying engine's default behavior.

Partitioning Parquet files

New in version 0.24.0.

Parquet supports partitioning of data based on the values of one or more columns.

```
In [519]: df = pd.DataFrame({"a": [0, 0, 1, 1], "b": [0, 1, 0, 1]})

In [520]: df.to_parquet(path="test", engine="pyarrow", partition_cols=["a"],␣
↪compression=None)
```

The `path` specifies the parent directory to which data will be saved. The `partition_cols` are the column names by which the dataset will be partitioned. Columns are partitioned in the order they are given. The partition splits are determined by the unique values in the partition columns. The above example creates a partitioned dataset that may look like:

```
test
├── a=0
│   ├── 0bac803e32dc42ae83fddfd029cbdebc.parquet
│   └── ...
└── a=1
    ├── e6ab24a4f45147b49b54a662f0c412a3.parquet
    └── ...
```

2.4.13 ORC

New in version 1.0.0.

Similar to the *parquet* format, the ORC Format is a binary columnar serialization for data frames. It is designed to make reading data frames efficient. pandas provides *only* a reader for the ORC format, *`read_orc()`*. This requires the pyarrow library.

2.4.14 SQL queries

The `pandas.io.sql` module provides a collection of query wrappers to both facilitate data retrieval and to reduce dependency on DB-specific API. Database abstraction is provided by SQLAlchemy if installed. In addition you will need a driver library for your database. Examples of such drivers are psycopg2 for PostgreSQL or pymysql for MySQL. For SQLite this is included in Python's standard library by default. You can find an overview of supported drivers for each SQL dialect in the SQLAlchemy docs.

If SQLAlchemy is not installed, a fallback is only provided for sqlite (and for mysql for backwards compatibility, but this is deprecated and will be removed in a future version). This mode requires a Python database adapter which respect the Python DB-API.

See also some *cookbook examples* for some advanced strategies.

The key functions are:

read_sql_table(table_name, con[, schema, ...])	Read SQL database table into a DataFrame.
read_sql_query(sql, con[, index_col, ...])	Read SQL query into a DataFrame.
read_sql(sql, con[, index_col, ...])	Read SQL query or database table into a DataFrame.
DataFrame.to_sql(name, con[, schema, ...])	Write records stored in a DataFrame to a SQL database.

Note: The function *read_sql()* is a convenience wrapper around *read_sql_table()* and *read_sql_query()* (and for backward compatibility) and will delegate to specific function depending on the provided input (database table name or sql query). Table names do not need to be quoted if they have special characters.

In the following example, we use the SQlite SQL database engine. You can use a temporary SQLite database where data are stored in "memory".

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For more information on `create_engine()` and the URI formatting, see the examples below and the SQLAlchemy documentation

```
In [521]: from sqlalchemy import create_engine

# Create your engine.
In [522]: engine = create_engine("sqlite:///:memory:")
```

If you want to manage your own connections you can pass one of those instead:

```
with engine.connect() as conn, conn.begin():
    data = pd.read_sql_table("data", conn)
```

Writing DataFrames

Assuming the following data is in a `DataFrame` `data`, we can insert it into the database using *to_sql()*.

id	Date	Col_1	Col_2	Col_3
26	2012-10-18	X	25.7	True
42	2012-10-19	Y	-12.4	False
63	2012-10-20	Z	5.73	True

```
In [523]: data
Out[523]:
   id       Date Col_1  Col_2  Col_3
0  26 2010-10-18     X  27.50   True
1  42 2010-10-19     Y -12.50  False
2  63 2010-10-20     Z   5.73   True

In [524]: data.to_sql("data", engine)
```

With some databases, writing large DataFrames can result in errors due to packet size limitations being exceeded. This can be avoided by setting the `chunksize` parameter when calling `to_sql`. For example, the following writes `data` to the database in batches of 1000 rows at a time:

```
In [525]: data.to_sql("data_chunked", engine, chunksize=1000)
```

SQL data types

to_sql() will try to map your data to an appropriate SQL data type based on the dtype of the data. When you have columns of dtype `object`, pandas will try to infer the data type.

You can always override the default type by specifying the desired SQL type of any of the columns by using the `dtype` argument. This argument needs a dictionary mapping column names to SQLAlchemy types (or strings for the sqlite3 fallback mode). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```
In [526]: from sqlalchemy.types import String

In [527]: data.to_sql("data_dtype", engine, dtype={"Col_1": String})
```

Note: Due to the limited support for timedelta's in the different database flavors, columns with type `timedelta64` will be written as integer values as nanoseconds to the database and a warning will be raised.

Note: Columns of `category` dtype will be converted to the dense representation as you would get with `np.asarray(categorical)` (e.g. for string categories this gives an array of strings). Because of this, reading the database table back in does **not** generate a categorical.

Datetime data types

Using SQLAlchemy, *to_sql()* is capable of writing datetime data that is timezone naive or timezone aware. However, the resulting data stored in the database ultimately depends on the supported data type for datetime data of the database system being used.

The following table lists supported data types for datetime data for some common databases. Other database dialects may have different data types for datetime data.

Database	SQL Datetime Types	Timezone Support
SQLite	`TEXT`	No
MySQL	`TIMESTAMP` or `DATETIME`	No
PostgreSQL	`TIMESTAMP` or `TIMESTAMP WITH TIME ZONE`	Yes

When writing timezone aware data to databases that do not support timezones, the data will be written as timezone naive timestamps that are in local time with respect to the timezone.

read_sql_table() is also capable of reading datetime data that is timezone aware or naive. When reading `TIMESTAMP WITH TIME ZONE` types, pandas will convert the data to UTC.

Insertion method

New in version 0.24.0.

The parameter `method` controls the SQL insertion clause used. Possible values are:

- `None`: Uses standard SQL `INSERT` clause (one per row).
- `'multi'`: Pass multiple values in a single `INSERT` clause. It uses a *special* SQL syntax not supported by all backends. This usually provides better performance for analytic databases like *Presto* and *Redshift*, but has worse performance for traditional SQL backend if the table contains many columns. For more information check the SQLAlchemy documentation.
- callable with signature `(pd_table, conn, keys, data_iter)`: This can be used to implement a more performant insertion method based on specific backend dialect features.

Example of a callable using PostgreSQL COPY clause:

```
# Alternative to_sql() *method* for DBs that support COPY FROM
import csv
from io import StringIO

def psql_insert_copy(table, conn, keys, data_iter):
    """
    Execute SQL statement inserting data

    Parameters
    ----------
    table : pandas.io.sql.SQLTable
    conn : sqlalchemy.engine.Engine or sqlalchemy.engine.Connection
    keys : list of str
        Column names
    data_iter : Iterable that iterates the values to be inserted
    """
    # gets a DBAPI connection that can provide a cursor
    dbapi_conn = conn.connection
    with dbapi_conn.cursor() as cur:
        s_buf = StringIO()
        writer = csv.writer(s_buf)
        writer.writerows(data_iter)
        s_buf.seek(0)

        columns = ', '.join('"{}"'.format(k) for k in keys)
        if table.schema:
            table_name = '{}.{}'.format(table.schema, table.name)
        else:
            table_name = table.name

        sql = 'COPY {} ({}) FROM STDIN WITH CSV'.format(
            table_name, columns)
        cur.copy_expert(sql=sql, file=s_buf)
```

Reading tables

read_sql_table() will read a database table given the table name and optionally a subset of columns to read.

Note: In order to use *read_sql_table()*, you **must** have the SQLAlchemy optional dependency installed.

```
In [528]: pd.read_sql_table("data", engine)
Out[528]:
   index  id       Date Col_1  Col_2  Col_3
0      0  26 2010-10-18     X  27.50   True
1      1  42 2010-10-19     Y -12.50  False
2      2  63 2010-10-20     Z   5.73   True
```

Note: Note that pandas infers column dtypes from query outputs, and not by looking up data types in the physical database schema. For example, assume `userid` is an integer column in a table. Then, intuitively, `select userid ...` will return integer-valued series, while `select cast(userid as text) ...` will return object-valued (str) series. Accordingly, if the query output is empty, then all resulting columns will be returned as object-valued (since they are most general). If you foresee that your query will sometimes generate an empty result, you may want to explicitly typecast afterwards to ensure dtype integrity.

You can also specify the name of the column as the `DataFrame` index, and specify a subset of columns to be read.

```
In [529]: pd.read_sql_table("data", engine, index_col="id")
Out[529]:
    index       Date Col_1  Col_2  Col_3
id
26      0 2010-10-18     X  27.50   True
42      1 2010-10-19     Y -12.50  False
63      2 2010-10-20     Z   5.73   True

In [530]: pd.read_sql_table("data", engine, columns=["Col_1", "Col_2"])
Out[530]:
  Col_1  Col_2
0     X  27.50
1     Y -12.50
2     Z   5.73
```

And you can explicitly force columns to be parsed as dates:

```
In [531]: pd.read_sql_table("data", engine, parse_dates=["Date"])
Out[531]:
   index  id       Date Col_1  Col_2  Col_3
0      0  26 2010-10-18     X  27.50   True
1      1  42 2010-10-19     Y -12.50  False
2      2  63 2010-10-20     Z   5.73   True
```

If needed you can explicitly specify a format string, or a dict of arguments to pass to *pandas.to_datetime()*:

```
pd.read_sql_table("data", engine, parse_dates={"Date": "%Y-%m-%d"})
pd.read_sql_table(
    "data",
    engine,
    parse_dates={"Date": {"format": "%Y-%m-%d %H:%M:%S"}},
)
```

You can check if a table exists using `has_table()`

Schema support

Reading from and writing to different schema's is supported through the `schema` keyword in the *read_sql_table()* and *to_sql()* functions. Note however that this depends on the database flavor (sqlite does not have schema's). For example:

```
df.to_sql("table", engine, schema="other_schema")
pd.read_sql_table("table", engine, schema="other_schema")
```

Querying

You can query using raw SQL in the *read_sql_query()* function. In this case you must use the SQL variant appropriate for your database. When using SQLAlchemy, you can also pass SQLAlchemy Expression language constructs, which are database-agnostic.

```
In [532]: pd.read_sql_query("SELECT * FROM data", engine)
Out[532]:
   index  id                        Date Col_1  Col_2  Col_3
0      0  26  2010-10-18 00:00:00.000000     X  27.50      1
1      1  42  2010-10-19 00:00:00.000000     Y -12.50      0
2      2  63  2010-10-20 00:00:00.000000     Z   5.73      1
```

Of course, you can specify a more "complex" query.

```
In [533]: pd.read_sql_query("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;",␣
↪engine)
Out[533]:
   id Col_1  Col_2
0  42     Y  -12.5
```

The *read_sql_query()* function supports a `chunksize` argument. Specifying this will return an iterator through chunks of the query result:

```
In [534]: df = pd.DataFrame(np.random.randn(20, 3), columns=list("abc"))

In [535]: df.to_sql("data_chunks", engine, index=False)
```

```
In [536]: for chunk in pd.read_sql_query("SELECT * FROM data_chunks", engine,␣
↪chunksize=5):
   .....:     print(chunk)
   .....:
          a         b         c
0  0.092961 -0.674003  1.104153
1 -0.092732 -0.156246 -0.585167
2 -0.358119 -0.862331 -1.672907
3  0.550313 -1.507513 -0.617232
4  0.650576  1.033221  0.492464
          a         b         c
0 -1.627786 -0.692062  1.039548
1 -1.802313 -0.890905 -0.881794
2  0.630492  0.016739  0.014500
3 -0.438358  0.647275 -0.052075
```

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```
4  0.673137  1.227539  0.203534
          a         b         c
0  0.861658  0.867852 -0.465016
1  1.547012 -0.947189 -1.241043
2  0.070470  0.901320  0.937577
3  0.295770  1.420548 -0.005283
4 -1.518598 -0.730065  0.226497
          a         b         c
0 -2.061465  0.632115  0.853619
1  2.719155  0.139018  0.214557
2 -1.538924 -0.366973 -0.748801
3 -0.478137 -1.559153 -3.097759
4 -2.320335 -0.221090  0.119763
```

You can also run a plain query without creating a `DataFrame` with `execute()`. This is useful for queries that don't return values, such as INSERT. This is functionally equivalent to calling `execute` on the SQLAlchemy engine or db connection object. Again, you must use the SQL syntax variant appropriate for your database.

```
from pandas.io import sql

sql.execute("SELECT * FROM table_name", engine)
sql.execute(
    "INSERT INTO table_name VALUES(?, ?, ?)", engine, params=[("id", 1, 12.2, True)]
)
```

Engine connection examples

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to.

```
from sqlalchemy import create_engine

engine = create_engine("postgresql://scott:tiger@localhost:5432/mydatabase")

engine = create_engine("mysql+mysqldb://scott:tiger@localhost/foo")

engine = create_engine("oracle://scott:tiger@127.0.0.1:1521/sidname")

engine = create_engine("mssql+pyodbc://mydsn")

# sqlite://<nohostname>/<path>
# where <path> is relative:
engine = create_engine("sqlite:///foo.db")

# or absolute, starting with a slash:
engine = create_engine("sqlite:////absolute/path/to/foo.db")
```

For more information see the examples the SQLAlchemy documentation

Advanced SQLAlchemy queries

You can use SQLAlchemy constructs to describe your query.

Use `sqlalchemy.text()` to specify query parameters in a backend-neutral way

```
In [537]: import sqlalchemy as sa

In [538]: pd.read_sql(
   .....:     sa.text("SELECT * FROM data where Col_1=:col1"), engine, params={"col1":
↪ "X"}
   .....: )
   .....:
Out[538]:
   index  id                        Date Col_1  Col_2  Col_3
0      0  26  2010-10-18 00:00:00.000000     X   27.5      1
```

If you have an SQLAlchemy description of your database you can express where conditions using SQLAlchemy expressions

```
In [539]: metadata = sa.MetaData()

In [540]: data_table = sa.Table(
   .....:     "data",
   .....:     metadata,
   .....:     sa.Column("index", sa.Integer),
   .....:     sa.Column("Date", sa.DateTime),
   .....:     sa.Column("Col_1", sa.String),
   .....:     sa.Column("Col_2", sa.Float),
   .....:     sa.Column("Col_3", sa.Boolean),
   .....: )
   .....:

In [541]: pd.read_sql(sa.select([data_table]).where(data_table.c.Col_3 is True),␣
↪engine)
Out[541]:
Empty DataFrame
Columns: [index, Date, Col_1, Col_2, Col_3]
Index: []
```

You can combine SQLAlchemy expressions with parameters passed to *read_sql()* using `sqlalchemy.bindparam()`

```
In [542]: import datetime as dt

In [543]: expr = sa.select([data_table]).where(data_table.c.Date > sa.bindparam("date
↪"))

In [544]: pd.read_sql(expr, engine, params={"date": dt.datetime(2010, 10, 18)})
Out[544]:
   index       Date Col_1  Col_2  Col_3
0      1 2010-10-19     Y -12.50  False
1      2 2010-10-20     Z   5.73   True
```

Sqlite fallback

The use of sqlite is supported without using SQLAlchemy. This mode requires a Python database adapter which respect the Python DB-API.

You can create connections like so:

```
import sqlite3

con = sqlite3.connect(":memory:")
```

And then issue the following queries:

```
data.to_sql("data", con)
pd.read_sql_query("SELECT * FROM data", con)
```

2.4.15 Google BigQuery

Warning: Starting in 0.20.0, pandas has split off Google BigQuery support into the separate package `pandas-gbq`. You can `pip install pandas-gbq` to get it.

The `pandas-gbq` package provides functionality to read/write from Google BigQuery.

pandas integrates with this external package. if `pandas-gbq` is installed, you can use the pandas methods `pd.read_gbq` and `DataFrame.to_gbq`, which will call the respective functions from `pandas-gbq`.

Full documentation can be found here.

2.4.16 Stata format

Writing to stata format

The method `to_stata()` will write a DataFrame into a .dta file. The format version of this file is always 115 (Stata 12).

```
In [545]: df = pd.DataFrame(np.random.randn(10, 2), columns=list("AB"))

In [546]: df.to_stata("stata.dta")
```

Stata data files have limited data type support; only strings with 244 or fewer characters, `int8`, `int16`, `int32`, `float32` and `float64` can be stored in `.dta` files. Additionally, *Stata* reserves certain values to represent missing data. Exporting a non-missing value that is outside of the permitted range in Stata for a particular data type will retype the variable to the next larger size. For example, `int8` values are restricted to lie between -127 and 100 in Stata, and so variables with values above 100 will trigger a conversion to `int16`. `nan` values in floating points data types are stored as the basic missing data type (`.` in *Stata*).

Note: It is not possible to export missing data values for integer data types.

The *Stata* writer gracefully handles other data types including `int64`, `bool`, `uint8`, `uint16`, `uint32` by casting to the smallest supported type that can represent the data. For example, data with a type of `uint8` will be cast to

`int8` if all values are less than 100 (the upper bound for non-missing `int8` data in *Stata*), or, if values are outside of this range, the variable is cast to `int16`.

Warning: Conversion from `int64` to `float64` may result in a loss of precision if `int64` values are larger than 2**53.

Warning: `StataWriter` and `to_stata()` only support fixed width strings containing up to 244 characters, a limitation imposed by the version 115 dta file format. Attempting to write *Stata* dta files with strings longer than 244 characters raises a `ValueError`.

Reading from Stata format

The top-level function `read_stata` will read a dta file and return either a `DataFrame` or a `StataReader` that can be used to read the file incrementally.

```
In [547]: pd.read_stata("stata.dta")
Out[547]:
   index         A         B
0      0  0.608228  1.064810
1      1 -0.780506 -2.736887
2      2  0.143539  1.170191
3      3 -1.573076  0.075792
4      4 -1.722223 -0.774650
5      5  0.803627  0.221665
6      6  0.584637  0.147264
7      7  1.057825 -0.284136
8      8  0.912395  1.552808
9      9  0.189376 -0.109830
```

Specifying a `chunksize` yields a `StataReader` instance that can be used to read `chunksize` lines from the file at a time. The `StataReader` object can be used as an iterator.

```
In [548]: with pd.read_stata("stata.dta", chunksize=3) as reader:
   .....:     for df in reader:
   .....:         print(df.shape)
   .....:
(3, 3)
(3, 3)
(3, 3)
(1, 3)
```

For more fine-grained control, use `iterator=True` and specify `chunksize` with each call to `read()`.

```
In [549]: with pd.read_stata("stata.dta", iterator=True) as reader:
   .....:     chunk1 = reader.read(5)
   .....:     chunk2 = reader.read(5)
   .....:
```

Currently the `index` is retrieved as a column.

The parameter `convert_categoricals` indicates whether value labels should be read and used to create a `Categorical` variable from them. Value labels can also be retrieved by the function `value_labels`, which requires `read()` to be called before use.

The parameter `convert_missing` indicates whether missing value representations in Stata should be preserved. If `False` (the default), missing values are represented as `np.nan`. If `True`, missing values are represented using `StataMissingValue` objects, and columns containing missing values will have `object` data type.

Note: *`read_stata()`* and `StataReader` support .dta formats 113-115 (Stata 10-12), 117 (Stata 13), and 118 (Stata 14).

Note: Setting `preserve_dtypes=False` will upcast to the standard pandas data types: `int64` for all integer types and `float64` for floating point data. By default, the Stata data types are preserved when importing.

Categorical data

`Categorical` data can be exported to *Stata* data files as value labeled data. The exported data consists of the underlying category codes as integer data values and the categories as value labels. *Stata* does not have an explicit equivalent to a `Categorical` and information about *whether* the variable is ordered is lost when exporting.

Warning: *Stata* only supports string value labels, and so `str` is called on the categories when exporting data. Exporting `Categorical` variables with non-string categories produces a warning, and can result a loss of information if the `str` representations of the categories are not unique.

Labeled data can similarly be imported from *Stata* data files as `Categorical` variables using the keyword argument `convert_categoricals` (`True` by default). The keyword argument `order_categoricals` (`True` by default) determines whether imported `Categorical` variables are ordered.

Note: When importing categorical data, the values of the variables in the *Stata* data file are not preserved since `Categorical` variables always use integer data types between `-1` and `n-1` where `n` is the number of categories. If the original values in the *Stata* data file are required, these can be imported by setting `convert_categoricals=False`, which will import original data (but not the variable labels). The original values can be matched to the imported categorical data since there is a simple mapping between the original *Stata* data values and the category codes of imported Categorical variables: missing values are assigned code `-1`, and the smallest original value is assigned `0`, the second smallest is assigned `1` and so on until the largest original value is assigned the code `n-1`.

Note: *Stata* supports partially labeled series. These series have value labels for some but not all data values. Importing a partially labeled series will produce a `Categorical` with string categories for the values that are labeled and numeric categories for values with no label.

2.4.17 SAS formats

The top-level function *read_sas()* can read (but not write) SAS XPORT (.xpt) and (since *v0.18.0*) SAS7BDAT (.sas7bdat) format files.

SAS files only contain two value types: ASCII text and floating point values (usually 8 bytes but sometimes truncated). For xport files, there is no automatic type conversion to integers, dates, or categoricals. For SAS7BDAT files, the format codes may allow date variables to be automatically converted to dates. By default the whole file is read and returned as a `DataFrame`.

Specify a `chunksize` or use `iterator=True` to obtain reader objects (`XportReader` or `SAS7BDATReader`) for incrementally reading the file. The reader objects also have attributes that contain additional information about the file and its variables.

Read a SAS7BDAT file:

```
df = pd.read_sas("sas_data.sas7bdat")
```

Obtain an iterator and read an XPORT file 100,000 lines at a time:

```
def do_something(chunk):
    pass


with pd.read_sas("sas_xport.xpt", chunk=100000) as rdr:
    for chunk in rdr:
        do_something(chunk)
```

The specification for the xport file format is available from the SAS web site.

No official documentation is available for the SAS7BDAT format.

2.4.18 SPSS formats

New in version 0.25.0.

The top-level function *read_spss()* can read (but not write) SPSS SAV (.sav) and ZSAV (.zsav) format files.

SPSS files contain column names. By default the whole file is read, categorical columns are converted into `pd.Categorical`, and a `DataFrame` with all columns is returned.

Specify the `usecols` parameter to obtain a subset of columns. Specify `convert_categoricals=False` to avoid converting categorical columns into `pd.Categorical`.

Read an SPSS file:

```
df = pd.read_spss("spss_data.sav")
```

Extract a subset of columns contained in `usecols` from an SPSS file and avoid converting categorical columns into `pd.Categorical`:

```
df = pd.read_spss(
    "spss_data.sav",
    usecols=["foo", "bar"],
    convert_categoricals=False,
)
```

More information about the SAV and ZSAV file formats is available here.

2.4.19 Other file formats

pandas itself only supports IO with a limited set of file formats that map cleanly to its tabular data model. For reading and writing other file formats into and from pandas, we recommend these packages from the broader community.

netCDF

xarray provides data structures inspired by the pandas `DataFrame` for working with multi-dimensional datasets, with a focus on the netCDF file format and easy conversion to and from pandas.

2.4.20 Performance considerations

This is an informal comparison of various IO methods, using pandas 0.24.2. Timings are machine dependent and small differences should be ignored.

```
In [1]: sz = 1000000
In [2]: df = pd.DataFrame({'A': np.random.randn(sz), 'B': [1] * sz})

In [3]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 2 columns):
A    1000000 non-null float64
B    1000000 non-null int64
dtypes: float64(1), int64(1)
memory usage: 15.3 MB
```

The following test functions will be used below to compare the performance of several IO methods:

```
import numpy as np

import os

sz = 1000000
df = pd.DataFrame({"A": np.random.randn(sz), "B": [1] * sz})

sz = 1000000
np.random.seed(42)
df = pd.DataFrame({"A": np.random.randn(sz), "B": [1] * sz})


def test_sql_write(df):
    if os.path.exists("test.sql"):
        os.remove("test.sql")
    sql_db = sqlite3.connect("test.sql")
    df.to_sql(name="test_table", con=sql_db)
    sql_db.close()


def test_sql_read():
    sql_db = sqlite3.connect("test.sql")
    pd.read_sql_query("select * from test_table", sql_db)
    sql_db.close()
```

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```
def test_hdf_fixed_write(df):
    df.to_hdf("test_fixed.hdf", "test", mode="w")


def test_hdf_fixed_read():
    pd.read_hdf("test_fixed.hdf", "test")


def test_hdf_fixed_write_compress(df):
    df.to_hdf("test_fixed_compress.hdf", "test", mode="w", complib="blosc")


def test_hdf_fixed_read_compress():
    pd.read_hdf("test_fixed_compress.hdf", "test")


def test_hdf_table_write(df):
    df.to_hdf("test_table.hdf", "test", mode="w", format="table")


def test_hdf_table_read():
    pd.read_hdf("test_table.hdf", "test")


def test_hdf_table_write_compress(df):
    df.to_hdf(
        "test_table_compress.hdf", "test", mode="w", complib="blosc", format="table"
    )


def test_hdf_table_read_compress():
    pd.read_hdf("test_table_compress.hdf", "test")


def test_csv_write(df):
    df.to_csv("test.csv", mode="w")


def test_csv_read():
    pd.read_csv("test.csv", index_col=0)


def test_feather_write(df):
    df.to_feather("test.feather")


def test_feather_read():
    pd.read_feather("test.feather")


def test_pickle_write(df):
    df.to_pickle("test.pkl")


def test_pickle_read():
    pd.read_pickle("test.pkl")
```

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```
def test_pickle_write_compress(df):
    df.to_pickle("test.pkl.compress", compression="xz")


def test_pickle_read_compress():
    pd.read_pickle("test.pkl.compress", compression="xz")


def test_parquet_write(df):
    df.to_parquet("test.parquet")


def test_parquet_read():
    pd.read_parquet("test.parquet")
```

When writing, the top three functions in terms of speed are `test_feather_write`, `test_hdf_fixed_write` and `test_hdf_fixed_write_compress`.

```
In [4]: %timeit test_sql_write(df)
3.29 s ± 43.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [5]: %timeit test_hdf_fixed_write(df)
19.4 ms ± 560 µs per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [6]: %timeit test_hdf_fixed_write_compress(df)
19.6 ms ± 308 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [7]: %timeit test_hdf_table_write(df)
449 ms ± 5.61 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [8]: %timeit test_hdf_table_write_compress(df)
448 ms ± 11.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [9]: %timeit test_csv_write(df)
3.66 s ± 26.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [10]: %timeit test_feather_write(df)
9.75 ms ± 117 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [11]: %timeit test_pickle_write(df)
30.1 ms ± 229 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [12]: %timeit test_pickle_write_compress(df)
4.29 s ± 15.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [13]: %timeit test_parquet_write(df)
67.6 ms ± 706 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

When reading, the top three functions in terms of speed are `test_feather_read`, `test_pickle_read` and `test_hdf_fixed_read`.

```
In [14]: %timeit test_sql_read()
1.77 s ± 17.7 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [15]: %timeit test_hdf_fixed_read()
```

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```
19.4 ms ± 436 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [16]: %timeit test_hdf_fixed_read_compress()
19.5 ms ± 222 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [17]: %timeit test_hdf_table_read()
38.6 ms ± 857 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [18]: %timeit test_hdf_table_read_compress()
38.8 ms ± 1.49 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [19]: %timeit test_csv_read()
452 ms ± 9.04 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [20]: %timeit test_feather_read()
12.4 ms ± 99.7 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [21]: %timeit test_pickle_read()
18.4 ms ± 191 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [22]: %timeit test_pickle_read_compress()
915 ms ± 7.48 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [23]: %timeit test_parquet_read()
24.4 ms ± 146 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

The files `test.pkl.compress`, `test.parquet` and `test.feather` took the least space on disk (in bytes).

```
29519500 Oct 10 06:45 test.csv
16000248 Oct 10 06:45 test.feather
8281983  Oct 10 06:49 test.parquet
16000857 Oct 10 06:47 test.pkl
7552144  Oct 10 06:48 test.pkl.compress
34816000 Oct 10 06:42 test.sql
24009288 Oct 10 06:43 test_fixed.hdf
24009288 Oct 10 06:43 test_fixed_compress.hdf
24458940 Oct 10 06:44 test_table.hdf
24458940 Oct 10 06:44 test_table_compress.hdf
```

2.5 Indexing and selecting data

The axis labeling information in pandas objects serves many purposes:

- Identifies data (i.e. provides *metadata*) using known indicators, important for analysis, visualization, and interactive console display.
- Enables automatic and explicit data alignment.
- Allows intuitive getting and setting of subsets of the data set.

In this section, we will focus on the final point: namely, how to slice, dice, and generally get and set subsets of pandas objects. The primary focus will be on Series and DataFrame as they have received more development attention in this area.

Note: The Python and NumPy indexing operators `[]` and attribute operator `.` provide quick and easy access to pandas

data structures across a wide range of use cases. This makes interactive work intuitive, as there's little new to learn if you already know how to deal with Python dictionaries and NumPy arrays. However, since the type of the data to be accessed isn't known in advance, directly using standard operators has some optimization limits. For production code, we recommended that you take advantage of the optimized pandas data access methods exposed in this chapter.

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See *Returning a View versus Copy*.

See the *MultiIndex / Advanced Indexing* for `MultiIndex` and more advanced indexing documentation.

See the *cookbook* for some advanced strategies.

2.5.1 Different choices for indexing

Object selection has had a number of user-requested additions in order to support more explicit location based indexing. pandas now supports three types of multi-axis indexing.

- `.loc` is primarily label based, but may also be used with a boolean array. `.loc` will raise `KeyError` when the items are not found. Allowed inputs are:
  - A single label, e.g. `5` or `'a'` (Note that `5` is interpreted as a *label* of the index. This use is **not** an integer position along the index.).
  - A list or array of labels `['a', 'b', 'c']`.
  - A slice object with labels `'a':'f'` (Note that contrary to usual Python slices, **both** the start and the stop are included, when present in the index! See *Slicing with labels* and *Endpoints are inclusive*.)
  - A boolean array (any `NA` values will be treated as `False`).
  - A `callable` function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

  See more at *Selection by Label*.
- `.iloc` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array. `.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing. (this conforms with Python/NumPy *slice* semantics). Allowed inputs are:
  - An integer e.g. `5`.
  - A list or array of integers `[4, 3, 0]`.
  - A slice object with ints `1:7`.
  - A boolean array (any `NA` values will be treated as `False`).
  - A `callable` function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

  See more at *Selection by Position*, *Advanced Indexing* and *Advanced Hierarchical*.
- `.loc`, `.iloc`, and also `[]` indexing can accept a `callable` as indexer. See more at *Selection By Callable*.

Getting values from an object with multi-axes selection uses the following notation (using `.loc` as an example, but the following applies to `.iloc` as well). Any of the axes accessors may be the null slice `:`. Axes left out of the specification are assumed to be `:`, e.g. `p.loc['a']` is equivalent to `p.loc['a', :, :]`.

Object Type	Indexers
Series	`s.loc[indexer]`
DataFrame	`df.loc[row_indexer,column_indexer]`

2.5.2 Basics

As mentioned when introducing the data structures in the *last section*, the primary function of indexing with `[]` (a.k.a. `__getitem__` for those familiar with implementing class behavior in Python) is selecting out lower-dimensional slices. The following table shows return type values when indexing pandas objects with `[]`:

Object Type	Selection	Return Value Type
Series	`series[label]`	scalar value
DataFrame	`frame[colname]`	`Series` corresponding to colname

Here we construct a simple time series data set to use for illustrating the indexing functionality:

```
In [1]: dates = pd.date_range('1/1/2000', periods=8)

In [2]: df = pd.DataFrame(np.random.randn(8, 4),
   ...:                   index=dates, columns=['A', 'B', 'C', 'D'])
   ...:

In [3]: df
Out[3]:
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
```

Note: None of the indexing functionality is time series specific unless specifically stated.

Thus, as per above, we have the most basic indexing using `[]`:

```
In [4]: s = df['A']

In [5]: s[dates[5]]
Out[5]: -0.6736897080883706
```

You can pass a list of columns to `[]` to select columns in that order. If a column is not contained in the DataFrame, an exception will be raised. Multiple columns can also be set in this manner:

```
In [6]: df
Out[6]:
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
```

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```
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885

In [7]: df[['B', 'A']] = df[['A', 'B']]

In [8]: df
Out[8]:
                   A         B         C         D
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
```

You may find this useful for applying a transform (in-place) to a subset of the columns.

Warning: pandas aligns all AXES when setting `Series` and `DataFrame` from `.loc`, and `.iloc`.

This will **not** modify `df` because the column alignment is before value assignment.

```
In [9]: df[['A', 'B']]
Out[9]:
                   A         B
2000-01-01 -0.282863  0.469112
2000-01-02 -0.173215  1.212112
2000-01-03 -2.104569 -0.861849
2000-01-04 -0.706771  0.721555
2000-01-05  0.567020 -0.424972
2000-01-06  0.113648 -0.673690
2000-01-07  0.577046  0.404705
2000-01-08 -1.157892 -0.370647

In [10]: df.loc[:, ['B', 'A']] = df[['A', 'B']]

In [11]: df[['A', 'B']]
Out[11]:
                   A         B
2000-01-01 -0.282863  0.469112
2000-01-02 -0.173215  1.212112
2000-01-03 -2.104569 -0.861849
2000-01-04 -0.706771  0.721555
2000-01-05  0.567020 -0.424972
2000-01-06  0.113648 -0.673690
2000-01-07  0.577046  0.404705
2000-01-08 -1.157892 -0.370647
```

The correct way to swap column values is by using raw values:

```
In [12]: df.loc[:, ['B', 'A']] = df[['A', 'B']].to_numpy()

In [13]: df[['A', 'B']]
Out[13]:
                   A         B
2000-01-01  0.469112 -0.282863
2000-01-02  1.212112 -0.173215
2000-01-03 -0.861849 -2.104569
2000-01-04  0.721555 -0.706771
2000-01-05 -0.424972  0.567020
2000-01-06 -0.673690  0.113648
2000-01-07  0.404705  0.577046
2000-01-08 -0.370647 -1.157892
```

2.5.3 Attribute access

You may access an index on a `Series` or column on a `DataFrame` directly as an attribute:

```
In [14]: sa = pd.Series([1, 2, 3], index=list('abc'))

In [15]: dfa = df.copy()
```

```
In [16]: sa.b
Out[16]: 2

In [17]: dfa.A
Out[17]:
2000-01-01    0.469112
2000-01-02    1.212112
2000-01-03   -0.861849
2000-01-04    0.721555
2000-01-05   -0.424972
2000-01-06   -0.673690
2000-01-07    0.404705
2000-01-08   -0.370647
Freq: D, Name: A, dtype: float64
```

```
In [18]: sa.a = 5

In [19]: sa
Out[19]:
a    5
b    2
c    3
dtype: int64

In [20]: dfa.A = list(range(len(dfa.index)))  # ok if A already exists

In [21]: dfa
Out[21]:
            A         B         C         D
2000-01-01  0 -0.282863 -1.509059 -1.135632
2000-01-02  1 -0.173215  0.119209 -1.044236
2000-01-03  2 -2.104569 -0.494929  1.071804
```

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```
2000-01-04  3 -0.706771 -1.039575  0.271860
2000-01-05  4  0.567020  0.276232 -1.087401
2000-01-06  5  0.113648 -1.478427  0.524988
2000-01-07  6  0.577046 -1.715002 -1.039268
2000-01-08  7 -1.157892 -1.344312  0.844885

In [22]: dfa['A'] = list(range(len(dfa.index)))  # use this form to create a new␣
↪column

In [23]: dfa
Out[23]:
             A         B         C         D
2000-01-01  0 -0.282863 -1.509059 -1.135632
2000-01-02  1 -0.173215  0.119209 -1.044236
2000-01-03  2 -2.104569 -0.494929  1.071804
2000-01-04  3 -0.706771 -1.039575  0.271860
2000-01-05  4  0.567020  0.276232 -1.087401
2000-01-06  5  0.113648 -1.478427  0.524988
2000-01-07  6  0.577046 -1.715002 -1.039268
2000-01-08  7 -1.157892 -1.344312  0.844885
```

Warning:

- You can use this access only if the index element is a valid Python identifier, e.g. `s.1` is not allowed. See here for an explanation of valid identifiers.
- The attribute will not be available if it conflicts with an existing method name, e.g. `s.min` is not allowed, but `s['min']` is possible.
- Similarly, the attribute will not be available if it conflicts with any of the following list: `index`, `major_axis`, `minor_axis`, `items`.
- In any of these cases, standard indexing will still work, e.g. `s['1']`, `s['min']`, and `s['index']` will access the corresponding element or column.

If you are using the IPython environment, you may also use tab-completion to see these accessible attributes.

You can also assign a `dict` to a row of a `DataFrame`:

```
In [24]: x = pd.DataFrame({'x': [1, 2, 3], 'y': [3, 4, 5]})

In [25]: x.iloc[1] = {'x': 9, 'y': 99}

In [26]: x
Out[26]:
   x   y
0  1   3
1  9  99
2  3   5
```

You can use attribute access to modify an existing element of a Series or column of a DataFrame, but be careful; if you try to use attribute access to create a new column, it creates a new attribute rather than a new column. In 0.21.0 and later, this will raise a `UserWarning`:

```
In [1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In [2]: df.two = [4, 5, 6]
```

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```
UserWarning: Pandas doesn't allow Series to be assigned into nonexistent columns -␣
↪see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute_access
In [3]: df
Out[3]:
   one
0  1.0
1  2.0
2  3.0
```

2.5.4 Slicing ranges

The most robust and consistent way of slicing ranges along arbitrary axes is described in the *Selection by Position* section detailing the `.iloc` method. For now, we explain the semantics of slicing using the `[]` operator.

With Series, the syntax works exactly as with an ndarray, returning a slice of the values and the corresponding labels:

```
In [27]: s[:5]
Out[27]:
2000-01-01    0.469112
2000-01-02    1.212112
2000-01-03   -0.861849
2000-01-04    0.721555
2000-01-05   -0.424972
Freq: D, Name: A, dtype: float64

In [28]: s[::2]
Out[28]:
2000-01-01    0.469112
2000-01-03   -0.861849
2000-01-05   -0.424972
2000-01-07    0.404705
Freq: 2D, Name: A, dtype: float64

In [29]: s[::-1]
Out[29]:
2000-01-08   -0.370647
2000-01-07    0.404705
2000-01-06   -0.673690
2000-01-05   -0.424972
2000-01-04    0.721555
2000-01-03   -0.861849
2000-01-02    1.212112
2000-01-01    0.469112
Freq: -1D, Name: A, dtype: float64
```

Note that setting works as well:

```
In [30]: s2 = s.copy()

In [31]: s2[:5] = 0

In [32]: s2
Out[32]:
2000-01-01    0.000000
2000-01-02    0.000000
```

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```
2000-01-03    0.000000
2000-01-04    0.000000
2000-01-05    0.000000
2000-01-06   -0.673690
2000-01-07    0.404705
2000-01-08   -0.370647
Freq: D, Name: A, dtype: float64
```

With DataFrame, slicing inside of `[]` **slices the rows**. This is provided largely as a convenience since it is such a common operation.

```
In [33]: df[:3]
Out[33]:
                   A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804

In [34]: df[::-1]
Out[34]:
                   A         B         C         D
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
```

2.5.5 Selection by label

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See *Returning a View versus Copy*.

Warning:

`.loc` is strict when you present slicers that are not compatible (or convertible) with the index type. For example using integers in a `DatetimeIndex`. These will raise a `TypeError`.

```
In [35]: dfl = pd.DataFrame(np.random.randn(5, 4),
   ....:                    columns=list('ABCD'),
   ....:                    index=pd.date_range('20130101', periods=5))
   ....:

In [36]: dfl
Out[36]:
                   A         B         C         D
2013-01-01  1.075770 -0.109050  1.643563 -1.469388
2013-01-02  0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061
2013-01-05  0.895717  0.805244 -1.206412  2.565646
```

```
In [4]: dfl.loc[2:3]
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'>␣
↪with these indexers [2] of <type 'int'>
```

String likes in slicing *can* be convertible to the type of the index and lead to natural slicing.

```
In [37]: dfl.loc['20130102':'20130104']
Out[37]:
                   A         B         C         D
2013-01-02  0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061
```

Warning: Changed in version 1.0.0.

pandas will raise a `KeyError` if indexing with a list with missing labels. See *list-like Using loc with missing keys in a list is Deprecated*.

pandas provides a suite of methods in order to have **purely label based indexing**. This is a strict inclusion based protocol. Every label asked for must be in the index, or a `KeyError` will be raised. When slicing, both the start bound **AND** the stop bound are *included*, if present in the index. Integers are valid labels, but they refer to the label **and not the position**.

The `.loc` attribute is the primary access method. The following are valid inputs:

- A single label, e.g. `5` or `'a'` (Note that `5` is interpreted as a *label* of the index. This use is **not** an integer position along the index.).
- A list or array of labels `['a', 'b', 'c']`.
- A slice object with labels `'a':'f'` (Note that contrary to usual Python slices, **both** the start and the stop are included, when present in the index! See *Slicing with labels*.
- A boolean array.
- A `callable`, see *Selection By Callable*.

```
In [38]: s1 = pd.Series(np.random.randn(6), index=list('abcdef'))

In [39]: s1
Out[39]:
a    1.431256
b    1.340309
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64

In [40]: s1.loc['c':]
Out[40]:
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64
```

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```
In [41]: s1.loc['b']
Out[41]: 1.3403088497993827
```

Note that setting works as well:

```
In [42]: s1.loc['c':] = 0

In [43]: s1
Out[43]:
a    1.431256
b    1.340309
c    0.000000
d    0.000000
e    0.000000
f    0.000000
dtype: float64
```

With a DataFrame:

```
In [44]: df1 = pd.DataFrame(np.random.randn(6, 4),
   ....:                    index=list('abcdef'),
   ....:                    columns=list('ABCD'))
   ....:

In [45]: df1
Out[45]:
          A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
c  1.024180  0.569605  0.875906 -2.211372
d  0.974466 -2.006747 -0.410001 -0.078638
e  0.545952 -1.219217 -1.226825  0.769804
f -1.281247 -0.727707 -0.121306 -0.097883

In [46]: df1.loc[['a', 'b', 'd'], :]
Out[46]:
          A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
d  0.974466 -2.006747 -0.410001 -0.078638
```

Accessing via label slices:

```
In [47]: df1.loc['d':, 'A':'C']
Out[47]:
          A         B         C
d  0.974466 -2.006747 -0.410001
e  0.545952 -1.219217 -1.226825
f -1.281247 -0.727707 -0.121306
```

For getting a cross section using a label (equivalent to `df.xs('a')`):

```
In [48]: df1.loc['a']
Out[48]:
A    0.132003
```

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```
B   -0.827317
C   -0.076467
D   -1.187678
Name: a, dtype: float64
```

For getting values with a boolean array:

```
In [49]: df1.loc['a'] > 0
Out[49]:
A     True
B    False
C    False
D    False
Name: a, dtype: bool

In [50]: df1.loc[:, df1.loc['a'] > 0]
Out[50]:
          A
a  0.132003
b  1.130127
c  1.024180
d  0.974466
e  0.545952
f -1.281247
```

NA values in a boolean array propagate as `False`:

Changed in version 1.0.2.

```
In [51]: mask = pd.array([True, False, True, False, pd.NA, False], dtype="boolean")

In [52]: mask
Out[52]:
<BooleanArray>
[True, False, True, False, <NA>, False]
Length: 6, dtype: boolean

In [53]: df1[mask]
Out[53]:
          A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
c  1.024180  0.569605  0.875906 -2.211372
```

For getting a value explicitly:

```
# this is also equivalent to ``df1.at['a','A']``
In [54]: df1.loc['a', 'A']
Out[54]: 0.13200317033032932
```

Slicing with labels

When using `.loc` with slices, if both the start and the stop labels are present in the index, then elements *located* between the two (including them) are returned:

```
In [55]: s = pd.Series(list('abcde'), index=[0, 3, 2, 5, 4])

In [56]: s.loc[3:5]
Out[56]:
3    b
2    c
5    d
dtype: object
```

If at least one of the two is absent, but the index is sorted, and can be compared against start and stop labels, then slicing will still work as expected, by selecting labels which *rank* between the two:

```
In [57]: s.sort_index()
Out[57]:
0    a
2    c
3    b
4    e
5    d
dtype: object

In [58]: s.sort_index().loc[1:6]
Out[58]:
2    c
3    b
4    e
5    d
dtype: object
```

However, if at least one of the two is absent *and* the index is not sorted, an error will be raised (since doing otherwise would be computationally expensive, as well as potentially ambiguous for mixed type indexes). For instance, in the above example, `s.loc[1:6]` would raise `KeyError`.

For the rationale behind this behavior, see *Endpoints are inclusive*.

```
In [59]: s = pd.Series(list('abcdef'), index=[0, 3, 2, 5, 4, 2])

In [60]: s.loc[3:5]
Out[60]:
3    b
2    c
5    d
dtype: object
```

Also, if the index has duplicate labels *and* either the start or the stop label is dupulicated, an error will be raised. For instance, in the above example, `s.loc[2:5]` would raise a `KeyError`.

For more information about duplicate labels, see *Duplicate Labels*.

2.5.6 Selection by position

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See *Returning a View versus Copy*.

pandas provides a suite of methods in order to get **purely integer based indexing**. The semantics follow closely Python and NumPy slicing. These are `0-based` indexing. When slicing, the start bound is *included*, while the upper bound is *excluded*. Trying to use a non-integer, even a **valid** label will raise an `IndexError`.

The `.iloc` attribute is the primary access method. The following are valid inputs:

- An integer e.g. `5`.
- A list or array of integers `[4, 3, 0]`.
- A slice object with ints `1:7`.
- A boolean array.
- A `callable`, see *Selection By Callable*.

```
In [61]: s1 = pd.Series(np.random.randn(5), index=list(range(0, 10, 2)))

In [62]: s1
Out[62]:
0    0.695775
2    0.341734
4    0.959726
6   -1.110336
8   -0.619976
dtype: float64

In [63]: s1.iloc[:3]
Out[63]:
0    0.695775
2    0.341734
4    0.959726
dtype: float64

In [64]: s1.iloc[3]
Out[64]: -1.110336102891167
```

Note that setting works as well:

```
In [65]: s1.iloc[:3] = 0

In [66]: s1
Out[66]:
0    0.000000
2    0.000000
4    0.000000
6   -1.110336
8   -0.619976
dtype: float64
```

With a DataFrame:

```
In [67]: df1 = pd.DataFrame(np.random.randn(6, 4),
   ....:                    index=list(range(0, 12, 2)),
   ....:                    columns=list(range(0, 8, 2)))
   ....:

In [68]: df1
Out[68]:
           0         2         4         6
0   0.149748 -0.732339  0.687738  0.176444
2   0.403310 -0.154951  0.301624 -2.179861
4  -1.369849 -0.954208  1.462696 -1.743161
6  -0.826591 -0.345352  1.314232  0.690579
8   0.995761  2.396780  0.014871  3.357427
10 -0.317441 -1.236269  0.896171 -0.487602
```

Select via integer slicing:

```
In [69]: df1.iloc[:3]
Out[69]:
          0         2         4         6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161

In [70]: df1.iloc[1:5, 2:4]
Out[70]:
          4         6
2  0.301624 -2.179861
4  1.462696 -1.743161
6  1.314232  0.690579
8  0.014871  3.357427
```

Select via integer list:

```
In [71]: df1.iloc[[1, 3, 5], [1, 3]]
Out[71]:
           2         6
2  -0.154951 -2.179861
6  -0.345352  0.690579
10 -1.236269 -0.487602
```

```
In [72]: df1.iloc[1:3, :]
Out[72]:
          0         2         4         6
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
```

```
In [73]: df1.iloc[:, 1:3]
Out[73]:
           2         4
0  -0.732339  0.687738
2  -0.154951  0.301624
4  -0.954208  1.462696
6  -0.345352  1.314232
8   2.396780  0.014871
10 -1.236269  0.896171
```

```
# this is also equivalent to ``df1.iat[1,1]``
In [74]: df1.iloc[1, 1]
Out[74]: -0.1549507744249032
```

For getting a cross section using an integer position (equiv to `df.xs(1)`):

```
In [75]: df1.iloc[1]
Out[75]:
0    0.403310
2   -0.154951
4    0.301624
6   -2.179861
Name: 2, dtype: float64
```

Out of range slice indexes are handled gracefully just as in Python/NumPy.

```
# these are allowed in Python/NumPy.
In [76]: x = list('abcdef')

In [77]: x
Out[77]: ['a', 'b', 'c', 'd', 'e', 'f']

In [78]: x[4:10]
Out[78]: ['e', 'f']

In [79]: x[8:10]
Out[79]: []

In [80]: s = pd.Series(x)

In [81]: s
Out[81]:
0    a
1    b
2    c
3    d
4    e
5    f
dtype: object

In [82]: s.iloc[4:10]
Out[82]:
4    e
5    f
dtype: object

In [83]: s.iloc[8:10]
Out[83]: Series([], dtype: object)
```

Note that using slices that go out of bounds can result in an empty axis (e.g. an empty DataFrame being returned).

```
In [84]: df1 = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))

In [85]: df1
Out[85]:
          A         B
0 -0.082240 -2.182937
```

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```
1  0.380396  0.084844
2  0.432390  1.519970
3 -0.493662  0.600178
4  0.274230  0.132885

In [86]: df1.iloc[:, 2:3]
Out[86]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [87]: df1.iloc[:, 1:3]
Out[87]:
          B
0 -2.182937
1  0.084844
2  1.519970
3  0.600178
4  0.132885

In [88]: df1.iloc[4:6]
Out[88]:
         A         B
4  0.27423  0.132885
```

A single indexer that is out of bounds will raise an `IndexError`. A list of indexers where any element is out of bounds will raise an `IndexError`.

```
>>> df1.iloc[[4, 5, 6]]
IndexError: positional indexers are out-of-bounds

>>> df1.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds
```

2.5.7 Selection by callable

`.loc`, `.iloc`, and also `[]` indexing can accept a `callable` as indexer. The `callable` must be a function with one argument (the calling Series or DataFrame) that returns valid output for indexing.

```
In [89]: df1 = pd.DataFrame(np.random.randn(6, 4),
   ....:                    index=list('abcdef'),
   ....:                    columns=list('ABCD'))
   ....:

In [90]: df1
Out[90]:
          A         B         C         D
a -0.023688  2.410179  1.450520  0.206053
b -0.251905 -2.213588  1.063327  1.266143
c  0.299368 -0.863838  0.408204 -1.048089
d -0.025747 -0.988387  0.094055  1.262731
e  1.289997  0.082423 -0.055758  0.536580
f -0.489682  0.369374 -0.034571 -2.484478

In [91]: df1.loc[lambda df: df['A'] > 0, :]
```

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```
Out[91]:
          A         B         C         D
c  0.299368 -0.863838  0.408204 -1.048089
e  1.289997  0.082423 -0.055758  0.536580

In [92]: df1.loc[:, lambda df: ['A', 'B']]
Out[92]:
          A         B
a -0.023688  2.410179
b -0.251905 -2.213588
c  0.299368 -0.863838
d -0.025747 -0.988387
e  1.289997  0.082423
f -0.489682  0.369374

In [93]: df1.iloc[:, lambda df: [0, 1]]
Out[93]:
          A         B
a -0.023688  2.410179
b -0.251905 -2.213588
c  0.299368 -0.863838
d -0.025747 -0.988387
e  1.289997  0.082423
f -0.489682  0.369374

In [94]: df1[lambda df: df.columns[0]]
Out[94]:
a   -0.023688
b   -0.251905
c    0.299368
d   -0.025747
e    1.289997
f   -0.489682
Name: A, dtype: float64
```

You can use callable indexing in `Series`.

```
In [95]: df1['A'].loc[lambda s: s > 0]
Out[95]:
c    0.299368
e    1.289997
Name: A, dtype: float64
```

Using these methods / indexers, you can chain data selection operations without using a temporary variable.

```
In [96]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [97]: (bb.groupby(['year', 'team']).sum()
   ....:    .loc[lambda df: df['r'] > 100])
   ....:
Out[97]:
           stint    g    ab    r    h  X2b  X3b  hr    rbi    sb   cs   bb     so  ␣
↪ibb   hbp    sh    sf  gidp
year team                                                                          ␣
↪
2007 CIN       6  379   745  101  203   35    2  36  125.0  10.0  1.0  105  127.0  14.
↪0   1.0   1.0  15.0  18.0
```

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```
     DET       5  301  1062  162  283   54    4  37  144.0  24.0  7.0   97  176.0   3.
↪0   10.0   4.0   8.0  28.0
     HOU       4  311   926  109  218   47    6  14   77.0  10.0  4.0   60  212.0   3.
↪0    9.0  16.0   6.0  17.0
     LAN      11  413  1021  153  293   61    3  36  154.0   7.0  5.0  114  141.0   8.
↪0    9.0   3.0   8.0  29.0
     NYN      13  622  1854  240  509  101    3  61  243.0  22.0  4.0  174  310.0  24.
↪0   23.0  18.0  15.0  48.0
     SFN       5  482  1305  198  337   67    6  40  171.0  26.0  7.0  235  188.0  51.
↪0    8.0  16.0   6.0  41.0
     TEX       2  198   729  115  200   40    4  28  115.0  21.0  4.0   73  140.0   4.
↪0    5.0   2.0   8.0  16.0
     TOR       4  459  1408  187  378   96    2  58  223.0   4.0  2.0  190  265.0  16.
↪0   12.0   4.0  16.0  38.0
```

2.5.8 Combining positional and label-based indexing

If you wish to get the 0th and the 2nd elements from the index in the 'A' column, you can do:

```
In [98]: dfd = pd.DataFrame({'A': [1, 2, 3],
   ....:                     'B': [4, 5, 6]},
   ....:                    index=list('abc'))
   ....:

In [99]: dfd
Out[99]:
   A  B
a  1  4
b  2  5
c  3  6

In [100]: dfd.loc[dfd.index[[0, 2]], 'A']
Out[100]:
a    1
c    3
Name: A, dtype: int64
```

This can also be expressed using `.iloc`, by explicitly getting locations on the indexers, and using *positional* indexing to select things.

```
In [101]: dfd.iloc[[0, 2], dfd.columns.get_loc('A')]
Out[101]:
a    1
c    3
Name: A, dtype: int64
```

For getting *multiple* indexers, using `.get_indexer`:

```
In [102]: dfd.iloc[[0, 2], dfd.columns.get_indexer(['A', 'B'])]
Out[102]:
   A  B
a  1  4
c  3  6
```

2.5.9 Indexing with list with missing labels is deprecated

Warning: Changed in version 1.0.0.

Using `.loc` or `[]` with a list with one or more missing labels will no longer reindex, in favor of `.reindex`.

In prior versions, using `.loc[list-of-labels]` would work as long as *at least 1* of the keys was found (otherwise it would raise a `KeyError`). This behavior was changed and will now raise a `KeyError` if at least one label is missing. The recommended alternative is to use `.reindex()`.

For example.

```
In [103]: s = pd.Series([1, 2, 3])

In [104]: s
Out[104]:
0    1
1    2
2    3
dtype: int64
```

Selection with all keys found is unchanged.

```
In [105]: s.loc[[1, 2]]
Out[105]:
1    2
2    3
dtype: int64
```

Previous behavior

```
In [4]: s.loc[[1, 2, 3]]
Out[4]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

Current behavior

```
In [4]: s.loc[[1, 2, 3]]
Passing list-likes to .loc with any non-matching elements will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
↪listlike

Out[4]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

Reindexing

The idiomatic way to achieve selecting potentially not-found elements is via `.reindex()`. See also the section on *reindexing*.

```
In [106]: s.reindex([1, 2, 3])
Out[106]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

Alternatively, if you want to select only *valid* keys, the following is idiomatic and efficient; it is guaranteed to preserve the dtype of the selection.

```
In [107]: labels = [1, 2, 3]

In [108]: s.loc[s.index.intersection(labels)]
Out[108]:
1    2
2    3
dtype: int64
```

Having a duplicated index will raise for a `.reindex()`:

```
In [109]: s = pd.Series(np.arange(4), index=['a', 'a', 'b', 'c'])

In [110]: labels = ['c', 'd']
```

```
In [17]: s.reindex(labels)
ValueError: cannot reindex from a duplicate axis
```

Generally, you can intersect the desired labels with the current axis, and then reindex.

```
In [111]: s.loc[s.index.intersection(labels)].reindex(labels)
Out[111]:
c    3.0
d    NaN
dtype: float64
```

However, this would *still* raise if your resulting index is duplicated.

```
In [41]: labels = ['a', 'd']

In [42]: s.loc[s.index.intersection(labels)].reindex(labels)
ValueError: cannot reindex from a duplicate axis
```

2.5.10 Selecting random samples

A random selection of rows or columns from a Series or DataFrame with the *sample()* method. The method will sample rows by default, and accepts a specific number of rows/columns to return, or a fraction of rows.

```
In [112]: s = pd.Series([0, 1, 2, 3, 4, 5])

# When no arguments are passed, returns 1 row.
In [113]: s.sample()
Out[113]:
4    4
dtype: int64

# One may specify either a number of rows:
In [114]: s.sample(n=3)
Out[114]:
0    0
4    4
1    1
dtype: int64

# Or a fraction of the rows:
In [115]: s.sample(frac=0.5)
Out[115]:
5    5
3    3
1    1
dtype: int64
```

By default, `sample` will return each row at most once, but one can also sample with replacement using the `replace` option:

```
In [116]: s = pd.Series([0, 1, 2, 3, 4, 5])

# Without replacement (default):
In [117]: s.sample(n=6, replace=False)
Out[117]:
0    0
1    1
5    5
3    3
2    2
4    4
dtype: int64

# With replacement:
In [118]: s.sample(n=6, replace=True)
Out[118]:
0    0
4    4
3    3
2    2
4    4
4    4
dtype: int64
```

By default, each row has an equal probability of being selected, but if you want rows to have different probabilities, you can pass the `sample` function sampling weights as `weights`. These weights can be a list, a NumPy array, or a

Series, but they must be of the same length as the object you are sampling. Missing values will be treated as a weight of zero, and inf values are not allowed. If weights do not sum to 1, they will be re-normalized by dividing all weights by the sum of the weights. For example:

```
In [119]: s = pd.Series([0, 1, 2, 3, 4, 5])

In [120]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [121]: s.sample(n=3, weights=example_weights)
Out[121]:
5    5
4    4
3    3
dtype: int64

# Weights will be re-normalized automatically
In [122]: example_weights2 = [0.5, 0, 0, 0, 0, 0]

In [123]: s.sample(n=1, weights=example_weights2)
Out[123]:
0    0
dtype: int64
```

When applied to a DataFrame, you can use a column of the DataFrame as sampling weights (provided you are sampling rows and not columns) by simply passing the name of the column as a string.

```
In [124]: df2 = pd.DataFrame({'col1': [9, 8, 7, 6],
   .....:                     'weight_column': [0.5, 0.4, 0.1, 0]})
   .....:

In [125]: df2.sample(n=3, weights='weight_column')
Out[125]:
   col1  weight_column
1     8            0.4
0     9            0.5
2     7            0.1
```

`sample` also allows users to sample columns instead of rows using the `axis` argument.

```
In [126]: df3 = pd.DataFrame({'col1': [1, 2, 3], 'col2': [2, 3, 4]})

In [127]: df3.sample(n=1, axis=1)
Out[127]:
   col1
0     1
1     2
2     3
```

Finally, one can also set a seed for `sample`'s random number generator using the `random_state` argument, which will accept either an integer (as a seed) or a NumPy RandomState object.

```
In [128]: df4 = pd.DataFrame({'col1': [1, 2, 3], 'col2': [2, 3, 4]})

# With a given seed, the sample will always draw the same rows.
In [129]: df4.sample(n=2, random_state=2)
Out[129]:
   col1  col2
2     3     4
```

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```
1     2     3

In [130]: df4.sample(n=2, random_state=2)
Out[130]:
   col1  col2
2     3     4
1     2     3
```

2.5.11 Setting with enlargement

The `.loc/[]` operations can perform enlargement when setting a non-existent key for that axis.

In the `Series` case this is effectively an appending operation.

```
In [131]: se = pd.Series([1, 2, 3])

In [132]: se
Out[132]:
0    1
1    2
2    3
dtype: int64

In [133]: se[5] = 5.

In [134]: se
Out[134]:
0    1.0
1    2.0
2    3.0
5    5.0
dtype: float64
```

A `DataFrame` can be enlarged on either axis via `.loc`.

```
In [135]: dfi = pd.DataFrame(np.arange(6).reshape(3, 2),
   .....:                    columns=['A', 'B'])
   .....:

In [136]: dfi
Out[136]:
   A  B
0  0  1
1  2  3
2  4  5

In [137]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']

In [138]: dfi
Out[138]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
```

This is like an `append` operation on the `DataFrame`.

```
In [139]: dfi.loc[3] = 5

In [140]: dfi
Out[140]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

2.5.12 Fast scalar value getting and setting

Since indexing with `[]` must handle a lot of cases (single-label access, slicing, boolean indexing, etc.), it has a bit of overhead in order to figure out what you're asking for. If you only want to access a scalar value, the fastest way is to use the `at` and `iat` methods, which are implemented on all of the data structures.

Similarly to `loc`, `at` provides **label** based scalar lookups, while, `iat` provides **integer** based lookups analogously to `iloc`

```
In [141]: s.iat[5]
Out[141]: 5

In [142]: df.at[dates[5], 'A']
Out[142]: -0.6736897080883706

In [143]: df.iat[3, 0]
Out[143]: 0.7215551622443669
```

You can also set using these same indexers.

```
In [144]: df.at[dates[5], 'E'] = 7

In [145]: df.iat[3, 0] = 7
```

`at` may enlarge the object in-place as above if the indexer is missing.

```
In [146]: df.at[dates[-1] + pd.Timedelta('1 day'), 0] = 7

In [147]: df
Out[147]:
                   A         B         C         D    E    0
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632  NaN  NaN
2000-01-02  1.212112 -0.173215  0.119209 -1.044236  NaN  NaN
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804  NaN  NaN
2000-01-04  7.000000 -0.706771 -1.039575  0.271860  NaN  NaN
2000-01-05 -0.424972  0.567020  0.276232 -1.087401  NaN  NaN
2000-01-06 -0.673690  0.113648 -1.478427  0.524988  7.0  NaN
2000-01-07  0.404705  0.577046 -1.715002 -1.039268  NaN  NaN
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885  NaN  NaN
2000-01-09       NaN       NaN       NaN       NaN  NaN  7.0
```

2.5.13 Boolean indexing

Another common operation is the use of boolean vectors to filter the data. The operators are: `|` for `or`, `&` for `and`, and `~` for `not`. These **must** be grouped by using parentheses, since by default Python will evaluate an expression such as `df['A'] > 2 & df['B'] < 3` as `df['A'] > (2 & df['B']) < 3`, while the desired evaluation order is `(df['A'] > 2) & (df['B'] < 3)`.

Using a boolean vector to index a Series works exactly as in a NumPy ndarray:

```
In [148]: s = pd.Series(range(-3, 4))

In [149]: s
Out[149]:
0   -3
1   -2
2   -1
3    0
4    1
5    2
6    3
dtype: int64

In [150]: s[s > 0]
Out[150]:
4    1
5    2
6    3
dtype: int64

In [151]: s[(s < -1) | (s > 0.5)]
Out[151]:
0   -3
1   -2
4    1
5    2
6    3
dtype: int64

In [152]: s[~(s < 0)]
Out[152]:
3    0
4    1
5    2
6    3
dtype: int64
```

You may select rows from a DataFrame using a boolean vector the same length as the DataFrame's index (for example, something derived from one of the columns of the DataFrame):

```
In [153]: df[df['A'] > 0]
Out[153]:
                   A         B         C         D   E   0
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632 NaN NaN
2000-01-02  1.212112 -0.173215  0.119209 -1.044236 NaN NaN
2000-01-04  7.000000 -0.706771 -1.039575  0.271860 NaN NaN
2000-01-07  0.404705  0.577046 -1.715002 -1.039268 NaN NaN
```

List comprehensions and the `map` method of Series can also be used to produce more complex criteria:

```
In [154]: df2 = pd.DataFrame({'a': ['one', 'one', 'two', 'three', 'two', 'one', 'six
↪'],
   .....:                     'b': ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
   .....:                     'c': np.random.randn(7)})
   .....:

# only want 'two' or 'three'
In [155]: criterion = df2['a'].map(lambda x: x.startswith('t'))

In [156]: df2[criterion]
Out[156]:
       a  b         c
2    two  y  0.041290
3  three  x  0.361719
4    two  y -0.238075

# equivalent but slower
In [157]: df2[[x.startswith('t') for x in df2['a']]]
Out[157]:
       a  b         c
2    two  y  0.041290
3  three  x  0.361719
4    two  y -0.238075

# Multiple criteria
In [158]: df2[criterion & (df2['b'] == 'x')]
Out[158]:
       a  b         c
3  three  x  0.361719
```

With the choice methods *Selection by Label*, *Selection by Position*, and *Advanced Indexing* you may select along more than one axis using boolean vectors combined with other indexing expressions.

```
In [159]: df2.loc[criterion & (df2['b'] == 'x'), 'b':'c']
Out[159]:
   b         c
3  x  0.361719
```

Warning: `iloc` supports two kinds of boolean indexing. If the indexer is a boolean `Series`, an error will be raised. For instance, in the following example, `df.iloc[s.values, 1]` is ok. The boolean indexer is an array. But `df.iloc[s, 1]` would raise `ValueError`.

```
In [160]: df = pd.DataFrame([[1, 2], [3, 4], [5, 6]],
   .....:                   index=list('abc'),
   .....:                   columns=['A', 'B'])
   .....:

In [161]: s = (df['A'] > 2)

In [162]: s
Out[162]:
a    False
b     True
c     True
Name: A, dtype: bool

In [163]: df.loc[s, 'B']
```

```
Out[163]:
b    4
c    6
Name: B, dtype: int64

In [164]: df.iloc[s.values, 1]
Out[164]:
b    4
c    6
Name: B, dtype: int64
```

2.5.14 Indexing with isin

Consider the *isin()* method of `Series`, which returns a boolean vector that is true wherever the `Series` elements exist in the passed list. This allows you to select rows where one or more columns have values you want:

```
In [165]: s = pd.Series(np.arange(5), index=np.arange(5)[::-1], dtype='int64')

In [166]: s
Out[166]:
4    0
3    1
2    2
1    3
0    4
dtype: int64

In [167]: s.isin([2, 4, 6])
Out[167]:
4    False
3    False
2     True
1    False
0     True
dtype: bool

In [168]: s[s.isin([2, 4, 6])]
Out[168]:
2    2
0    4
dtype: int64
```

The same method is available for `Index` objects and is useful for the cases when you don't know which of the sought labels are in fact present:

```
In [169]: s[s.index.isin([2, 4, 6])]
Out[169]:
4    0
2    2
dtype: int64

# compare it to the following
In [170]: s.reindex([2, 4, 6])
Out[170]:
2    2.0
```

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```
4    0.0
6    NaN
dtype: float64
```

In addition to that, `MultiIndex` allows selecting a separate level to use in the membership check:

```
In [171]: s_mi = pd.Series(np.arange(6),
   .....:                  index=pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c
↪']]))
   .....:

In [172]: s_mi
Out[172]:
0  a    0
   b    1
   c    2
1  a    3
   b    4
   c    5
dtype: int64

In [173]: s_mi.iloc[s_mi.index.isin([(1, 'a'), (2, 'b'), (0, 'c')])]
Out[173]:
0  c    2
1  a    3
dtype: int64

In [174]: s_mi.iloc[s_mi.index.isin(['a', 'c', 'e'], level=1)]
Out[174]:
0  a    0
   c    2
1  a    3
   c    5
dtype: int64
```

DataFrame also has an *`isin()`* method. When calling `isin`, pass a set of values as either an array or dict. If values is an array, `isin` returns a DataFrame of booleans that is the same shape as the original DataFrame, with True wherever the element is in the sequence of values.

```
In [175]: df = pd.DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
   .....:                    'ids2': ['a', 'n', 'c', 'n']})
   .....:

In [176]: values = ['a', 'b', 1, 3]

In [177]: df.isin(values)
Out[177]:
    vals    ids   ids2
0   True   True   True
1  False   True  False
2   True  False  False
3  False  False  False
```

Oftentimes you'll want to match certain values with certain columns. Just make values a `dict` where the key is the column, and the value is a list of items you want to check for.

```
In [178]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}

In [179]: df.isin(values)
Out[179]:
    vals    ids   ids2
0   True   True  False
1  False   True  False
2   True  False  False
3  False  False  False
```

Combine DataFrame's `isin` with the `any()` and `all()` methods to quickly select subsets of your data that meet a given criteria. To select a row where each column meets its own criterion:

```
In [180]: values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}

In [181]: row_mask = df.isin(values).all(1)

In [182]: df[row_mask]
Out[182]:
   vals ids ids2
0     1   a    a
```

2.5.15 The `where()` Method and Masking

Selecting values from a Series with a boolean vector generally returns a subset of the data. To guarantee that selection output has the same shape as the original data, you can use the `where` method in `Series` and `DataFrame`.

To return only the selected rows:

```
In [183]: s[s > 0]
Out[183]:
3    1
2    2
1    3
0    4
dtype: int64
```

To return a Series of the same shape as the original:

```
In [184]: s.where(s > 0)
Out[184]:
4    NaN
3    1.0
2    2.0
1    3.0
0    4.0
dtype: float64
```

Selecting values from a DataFrame with a boolean criterion now also preserves input data shape. `where` is used under the hood as the implementation. The code below is equivalent to `df.where(df < 0)`.

```
In [185]: df[df < 0]
Out[185]:
                   A         B         C         D
2000-01-01 -2.104139 -1.309525       NaN       NaN
2000-01-02 -0.352480       NaN -1.192319       NaN
```

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```
2000-01-03 -0.864883       NaN -0.227870       NaN
2000-01-04       NaN -1.222082       NaN -1.233203
2000-01-05       NaN -0.605656 -1.169184       NaN
2000-01-06       NaN -0.948458       NaN -0.684718
2000-01-07 -2.670153 -0.114722       NaN -0.048048
2000-01-08       NaN       NaN -0.048788 -0.808838
```

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

```
In [186]: df.where(df < 0, -df)
Out[186]:
                   A         B         C         D
2000-01-01 -2.104139 -1.309525 -0.485855 -0.245166
2000-01-02 -0.352480 -0.390389 -1.192319 -1.655824
2000-01-03 -0.864883 -0.299674 -0.227870 -0.281059
2000-01-04 -0.846958 -1.222082 -0.600705 -1.233203
2000-01-05 -0.669692 -0.605656 -1.169184 -0.342416
2000-01-06 -0.868584 -0.948458 -2.297780 -0.684718
2000-01-07 -2.670153 -0.114722 -0.168904 -0.048048
2000-01-08 -0.801196 -1.392071 -0.048788 -0.808838
```

You may wish to set values based on some boolean criteria. This can be done intuitively like so:

```
In [187]: s2 = s.copy()

In [188]: s2[s2 < 0] = 0

In [189]: s2
Out[189]:
4    0
3    1
2    2
1    3
0    4
dtype: int64

In [190]: df2 = df.copy()

In [191]: df2[df2 < 0] = 0

In [192]: df2
Out[192]:
                   A         B         C         D
2000-01-01  0.000000  0.000000  0.485855  0.245166
2000-01-02  0.000000  0.390389  0.000000  1.655824
2000-01-03  0.000000  0.299674  0.000000  0.281059
2000-01-04  0.846958  0.000000  0.600705  0.000000
2000-01-05  0.669692  0.000000  0.000000  0.342416
2000-01-06  0.868584  0.000000  2.297780  0.000000
2000-01-07  0.000000  0.000000  0.168904  0.000000
2000-01-08  0.801196  1.392071  0.000000  0.000000
```

By default, `where` returns a modified copy of the data. There is an optional parameter `inplace` so that the original data can be modified without creating a copy:

```
In [193]: df_orig = df.copy()

In [194]: df_orig.where(df > 0, -df, inplace=True)

In [195]: df_orig
Out[195]:
                   A         B         C         D
2000-01-01  2.104139  1.309525  0.485855  0.245166
2000-01-02  0.352480  0.390389  1.192319  1.655824
2000-01-03  0.864883  0.299674  0.227870  0.281059
2000-01-04  0.846958  1.222082  0.600705  1.233203
2000-01-05  0.669692  0.605656  1.169184  0.342416
2000-01-06  0.868584  0.948458  2.297780  0.684718
2000-01-07  2.670153  0.114722  0.168904  0.048048
2000-01-08  0.801196  1.392071  0.048788  0.808838
```

Note: The signature for *DataFrame.where()* differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

```
In [196]: df.where(df < 0, -df) == np.where(df < 0, df, -df)
Out[196]:
                A     B     C     D
2000-01-01  True  True  True  True
2000-01-02  True  True  True  True
2000-01-03  True  True  True  True
2000-01-04  True  True  True  True
2000-01-05  True  True  True  True
2000-01-06  True  True  True  True
2000-01-07  True  True  True  True
2000-01-08  True  True  True  True
```

Alignment

Furthermore, `where` aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.loc` (but on the contents rather than the axis labels).

```
In [197]: df2 = df.copy()

In [198]: df2[df2[1:4] > 0] = 3

In [199]: df2
Out[199]:
                   A         B         C         D
2000-01-01 -2.104139 -1.309525  0.485855  0.245166
2000-01-02 -0.352480  3.000000 -1.192319  3.000000
2000-01-03 -0.864883  3.000000 -0.227870  3.000000
2000-01-04  3.000000 -1.222082  3.000000 -1.233203
2000-01-05  0.669692 -0.605656 -1.169184  0.342416
2000-01-06  0.868584 -0.948458  2.297780 -0.684718
2000-01-07 -2.670153 -0.114722  0.168904 -0.048048
2000-01-08  0.801196  1.392071 -0.048788 -0.808838
```

Where can also accept `axis` and `level` parameters to align the input when performing the `where`.

```
In [200]: df2 = df.copy()
```

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```
In [201]: df2.where(df2 > 0, df2['A'], axis='index')
Out[201]:
                   A         B         C         D
2000-01-01 -2.104139 -2.104139  0.485855  0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  0.846958  0.846958  0.600705  0.846958
2000-01-05  0.669692  0.669692  0.669692  0.342416
2000-01-06  0.868584  0.868584  2.297780  0.868584
2000-01-07 -2.670153 -2.670153  0.168904 -2.670153
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

This is equivalent to (but faster than) the following.

```
In [202]: df2 = df.copy()

In [203]: df.apply(lambda x, y: x.where(x > 0, y), y=df['A'])
Out[203]:
                   A         B         C         D
2000-01-01 -2.104139 -2.104139  0.485855  0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  0.846958  0.846958  0.600705  0.846958
2000-01-05  0.669692  0.669692  0.669692  0.342416
2000-01-06  0.868584  0.868584  2.297780  0.868584
2000-01-07 -2.670153 -2.670153  0.168904 -2.670153
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

`where` can accept a callable as condition and `other` arguments. The function must be with one argument (the calling Series or DataFrame) and that returns valid output as condition and `other` argument.

```
In [204]: df3 = pd.DataFrame({'A': [1, 2, 3],
   .....:                     'B': [4, 5, 6],
   .....:                     'C': [7, 8, 9]})
   .....:

In [205]: df3.where(lambda x: x > 4, lambda x: x + 10)
Out[205]:
    A   B  C
0  11  14  7
1  12   5  8
2  13   6  9
```

Mask

`mask()` is the inverse boolean operation of `where`.

```
In [206]: s.mask(s >= 0)
Out[206]:
4   NaN
3   NaN
2   NaN
1   NaN
0   NaN
```

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```
dtype: float64

In [207]: df.mask(df >= 0)
Out[207]:
                   A         B         C         D
2000-01-01 -2.104139 -1.309525       NaN       NaN
2000-01-02 -0.352480       NaN -1.192319       NaN
2000-01-03 -0.864883       NaN -0.227870       NaN
2000-01-04       NaN -1.222082       NaN -1.233203
2000-01-05       NaN -0.605656 -1.169184       NaN
2000-01-06       NaN -0.948458       NaN -0.684718
2000-01-07 -2.670153 -0.114722       NaN -0.048048
2000-01-08       NaN       NaN -0.048788 -0.808838
```

2.5.16 Setting with enlargement conditionally using `numpy()`

An alternative to *`where()`* is to use `numpy.where()`. Combined with setting a new column, you can use it to enlarge a dataframe where the values are determined conditionally.

Consider you have two choices to choose from in the following dataframe. And you want to set a new column color to 'green' when the second column has 'Z'. You can do the following:

```
In [208]: df = pd.DataFrame({'col1': list('ABBC'), 'col2': list('ZZXY')})

In [209]: df['color'] = np.where(df['col2'] == 'Z', 'green', 'red')

In [210]: df
Out[210]:
  col1 col2  color
0    A    Z  green
1    B    Z  green
2    B    X    red
3    C    Y    red
```

If you have multiple conditions, you can use `numpy.select()` to achieve that. Say corresponding to three conditions there are three choice of colors, with a fourth color as a fallback, you can do the following.

```
In [211]: conditions = [
   .....:     (df['col2'] == 'Z') & (df['col1'] == 'A'),
   .....:     (df['col2'] == 'Z') & (df['col1'] == 'B'),
   .....:     (df['col1'] == 'B')
   .....: ]
   .....:

In [212]: choices = ['yellow', 'blue', 'purple']

In [213]: df['color'] = np.select(conditions, choices, default='black')

In [214]: df
Out[214]:
  col1 col2   color
0    A    Z  yellow
1    B    Z    blue
2    B    X  purple
3    C    Y   black
```

2.5.17 The `query()` Method

DataFrame objects have a *query()* method that allows selection using an expression.

You can get the value of the frame where column `b` has values between the values of columns `a` and `c`. For example:

```
In [215]: n = 10

In [216]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [217]: df
Out[217]:
          a         b         c
0  0.438921  0.118680  0.863670
1  0.138138  0.577363  0.686602
2  0.595307  0.564592  0.520630
3  0.913052  0.926075  0.616184
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
6  0.792342  0.216974  0.564056
7  0.397890  0.454131  0.915716
8  0.074315  0.437913  0.019794
9  0.559209  0.502065  0.026437

# pure python
In [218]: df[(df['a'] < df['b']) & (df['b'] < df['c'])]
Out[218]:
          a         b         c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716

# query
In [219]: df.query('(a < b) & (b < c)')
Out[219]:
          a         b         c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716
```

Do the same thing but fall back on a named index if there is no column with the name `a`.

```
In [220]: df = pd.DataFrame(np.random.randint(n / 2, size=(n, 2)), columns=list('bc'))

In [221]: df.index.name = 'a'

In [222]: df
Out[222]:
   b  c
a
0  0  4
1  0  1
2  3  4
3  4  3
4  1  4
5  0  3
```

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```
6  0  1
7  3  4
8  2  3
9  1  1

In [223]: df.query('a < b and b < c')
Out[223]:
   b  c
a
2  3  4
```

If instead you don't want to or cannot name your index, you can use the name `index` in your query expression:

```
In [224]: df = pd.DataFrame(np.random.randint(n, size=(n, 2)), columns=list('bc'))

In [225]: df
Out[225]:
   b  c
0  3  1
1  3  0
2  5  6
3  5  2
4  7  4
5  0  1
6  2  5
7  0  1
8  6  0
9  7  9

In [226]: df.query('index < b < c')
Out[226]:
   b  c
2  5  6
```

Note: If the name of your index overlaps with a column name, the column name is given precedence. For example,

```
In [227]: df = pd.DataFrame({'a': np.random.randint(5, size=5)})

In [228]: df.index.name = 'a'

In [229]: df.query('a > 2')  # uses the column 'a', not the index
Out[229]:
   a
a
1  3
3  3
```

You can still use the index in a query expression by using the special identifier 'index':

```
In [230]: df.query('index > 2')
Out[230]:
   a
a
3  3
4  2
```

If for some reason you have a column named `index`, then you can refer to the index as `ilevel_0` as well, but at this point you should consider renaming your columns to something less ambiguous.

`MultiIndex` `query()` Syntax

You can also use the levels of a `DataFrame` with a *`MultiIndex`* as if they were columns in the frame:

```
In [231]: n = 10

In [232]: colors = np.random.choice(['red', 'green'], size=n)

In [233]: foods = np.random.choice(['eggs', 'ham'], size=n)

In [234]: colors
Out[234]:
array(['red', 'red', 'red', 'green', 'green', 'green', 'green', 'green',
       'green', 'green'], dtype='<U5')

In [235]: foods
Out[235]:
array(['ham', 'ham', 'eggs', 'eggs', 'eggs', 'ham', 'ham', 'eggs', 'eggs',
       'eggs'], dtype='<U4')

In [236]: index = pd.MultiIndex.from_arrays([colors, foods], names=['color', 'food'])

In [237]: df = pd.DataFrame(np.random.randn(n, 2), index=index)

In [238]: df
Out[238]:
                  0         1
color food
red   ham    0.194889 -0.381994
      ham    0.318587  2.089075
      eggs -0.728293 -0.090255
green eggs -0.748199  1.318931
      eggs -2.029766  0.792652
      ham    0.461007 -0.542749
      ham   -0.305384 -0.479195
      eggs   0.095031 -0.270099
      eggs -0.707140 -0.773882
      eggs   0.229453  0.304418

In [239]: df.query('color == "red"')
Out[239]:
                  0         1
color food
red   ham    0.194889 -0.381994
      ham    0.318587  2.089075
      eggs -0.728293 -0.090255
```

If the levels of the `MultiIndex` are unnamed, you can refer to them using special names:

```
In [240]: df.index.names = [None, None]

In [241]: df
Out[241]:
```

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```
                   0         1
red   ham    0.194889 -0.381994
      ham    0.318587  2.089075
      eggs  -0.728293 -0.090255
green eggs  -0.748199  1.318931
      eggs  -2.029766  0.792652
      ham    0.461007 -0.542749
      ham   -0.305384 -0.479195
      eggs   0.095031 -0.270099
      eggs  -0.707140 -0.773882
      eggs   0.229453  0.304418

In [242]: df.query('ilevel_0 == "red"')
Out[242]:
                0         1
red ham   0.194889 -0.381994
    ham   0.318587  2.089075
    eggs -0.728293 -0.090255
```

The convention is `ilevel_0`, which means "index level 0" for the 0th level of the `index`.

`query()` Use Cases

A use case for *`query()`* is when you have a collection of *`DataFrame`* objects that have a subset of column names (or index levels/names) in common. You can pass the same query to both frames *without* having to specify which frame you're interested in querying

```
In [243]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [244]: df
Out[244]:
          a         b         c
0  0.224283  0.736107  0.139168
1  0.302827  0.657803  0.713897
2  0.611185  0.136624  0.984960
3  0.195246  0.123436  0.627712
4  0.618673  0.371660  0.047902
5  0.480088  0.062993  0.185760
6  0.568018  0.483467  0.445289
7  0.309040  0.274580  0.587101
8  0.258993  0.477769  0.370255
9  0.550459  0.840870  0.304611

In [245]: df2 = pd.DataFrame(np.random.rand(n + 2, 3), columns=df.columns)

In [246]: df2
Out[246]:
           a         b         c
0   0.357579  0.229800  0.596001
1   0.309059  0.957923  0.965663
2   0.123102  0.336914  0.318616
3   0.526506  0.323321  0.860813
4   0.518736  0.486514  0.384724
5   0.190804  0.505723  0.614533
6   0.891939  0.623977  0.676639
```

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```
7   0.480559  0.378528  0.460858
8   0.420223  0.136404  0.141295
9   0.732206  0.419540  0.604675
10  0.604466  0.848974  0.896165
11  0.589168  0.920046  0.732716

In [247]: expr = '0.0 <= a <= c <= 0.5'

In [248]: map(lambda frame: frame.query(expr), [df, df2])
Out[248]: <map at 0x7f7110fdd910>
```

`query()` Python versus pandas Syntax Comparison

Full numpy-like syntax:

```
In [249]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=list('abc'))

In [250]: df
Out[250]:
   a  b  c
0  7  8  9
1  1  0  7
2  2  7  2
3  6  2  2
4  2  6  3
5  3  8  2
6  1  7  2
7  5  1  5
8  9  8  0
9  1  5  0

In [251]: df.query('(a < b) & (b < c)')
Out[251]:
   a  b  c
0  7  8  9

In [252]: df[(df['a'] < df['b']) & (df['b'] < df['c'])]
Out[252]:
   a  b  c
0  7  8  9
```

Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than `&` and `|`).

```
In [253]: df.query('a < b & b < c')
Out[253]:
   a  b  c
0  7  8  9
```

Use English instead of symbols:

```
In [254]: df.query('a < b and b < c')
Out[254]:
   a  b  c
0  7  8  9
```

Pretty close to how you might write it on paper:

```
In [255]: df.query('a < b < c')
Out[255]:
   a  b  c
0  7  8  9
```

The `in` and `not in` operators

`query()` also supports special use of Python's `in` and `not in` comparison operators, providing a succinct syntax for calling the `isin` method of a `Series` or `DataFrame`.

```
# get all rows where columns "a" and "b" have overlapping values
In [256]: df = pd.DataFrame({'a': list('aabbccddeeff'), 'b': list('aaaabbbbcccc'),
   .....:                    'c': np.random.randint(5, size=12),
   .....:                    'd': np.random.randint(9, size=12)})
   .....:

In [257]: df
Out[257]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
3   b  a  2  1
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

In [258]: df.query('a in b')
Out[258]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2

# How you'd do it in pure Python
In [259]: df[df['a'].isin(df['b'])]
Out[259]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2

In [260]: df.query('a not in b')
Out[260]:
    a  b  c  d
```

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```
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

# pure Python
In [261]: df[~df['a'].isin(df['b'])]
Out[261]:
    a  b  c  d
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2
```

You can combine this with other expressions for very succinct queries:

```
# rows where cols a and b have overlapping values
# and col c's values are less than col d's
In [262]: df.query('a in b and c < d')
Out[262]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
4  c  b  3  6
5  c  b  0  2

# pure Python
In [263]: df[df['b'].isin(df['a']) & (df['c'] < df['d'])]
Out[263]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
4   c  b  3  6
5   c  b  0  2
10  f  c  0  6
11  f  c  1  2
```

Note: Note that `in` and `not in` are evaluated in Python, since `numexpr` has no equivalent of this operation. However, **only the** `in`/`not in` **expression itself** is evaluated in vanilla Python. For example, in the expression

```
df.query('a in b + c + d')
```

`(b + c + d)` is evaluated by `numexpr` and *then* the `in` operation is evaluated in plain Python. In general, any operations that can be evaluated using `numexpr` will be.

Special use of the == operator with `list` objects

Comparing a `list` of values to a column using ==/!= works similarly to `in`/`not in`.

```
In [264]: df.query('b == ["a", "b", "c"]')
Out[264]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
3   b  a  2  1
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

# pure Python
In [265]: df[df['b'].isin(["a", "b", "c"])]
Out[265]:
    a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
3   b  a  2  1
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

In [266]: df.query('c == [1, 2]')
Out[266]:
    a  b  c  d
0   a  a  2  6
2   b  a  1  6
3   b  a  2  1
7   d  b  2  1
9   e  c  2  0
11  f  c  1  2

In [267]: df.query('c != [1, 2]')
Out[267]:
    a  b  c  d
1   a  a  4  7
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
8   e  c  4  3
10  f  c  0  6

# using in/not in
```

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```
In [268]: df.query('[1, 2] in c')
Out[268]:
    a  b  c  d
0   a  a  2  6
2   b  a  1  6
3   b  a  2  1
7   d  b  2  1
9   e  c  2  0
11  f  c  1  2

In [269]: df.query('[1, 2] not in c')
Out[269]:
    a  b  c  d
1   a  a  4  7
4   c  b  3  6
5   c  b  0  2
6   d  b  3  3
8   e  c  4  3
10  f  c  0  6

# pure Python
In [270]: df[df['c'].isin([1, 2])]
Out[270]:
    a  b  c  d
0   a  a  2  6
2   b  a  1  6
3   b  a  2  1
7   d  b  2  1
9   e  c  2  0
11  f  c  1  2
```

Boolean operators

You can negate boolean expressions with the word `not` or the `~` operator.

```
In [271]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [272]: df['bools'] = np.random.rand(len(df)) > 0.5

In [273]: df.query('~bools')
Out[273]:
          a         b         c  bools
2  0.697753  0.212799  0.329209  False
7  0.275396  0.691034  0.826619  False
8  0.190649  0.558748  0.262467  False

In [274]: df.query('not bools')
Out[274]:
          a         b         c  bools
2  0.697753  0.212799  0.329209  False
7  0.275396  0.691034  0.826619  False
8  0.190649  0.558748  0.262467  False

In [275]: df.query('not bools') == df[~df['bools']]
Out[275]:
```

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```
      a     b     c  bools
2  True  True  True   True
7  True  True  True   True
8  True  True  True   True
```

Of course, expressions can be arbitrarily complex too:

```
# short query syntax
In [276]: shorter = df.query('a < b < c and (not bools) or bools > 2')

# equivalent in pure Python
In [277]: longer = df[(df['a'] < df['b'])
   .....:             & (df['b'] < df['c'])
   .....:             & (~df['bools'])
   .....:             | (df['bools'] > 2)]
   .....:

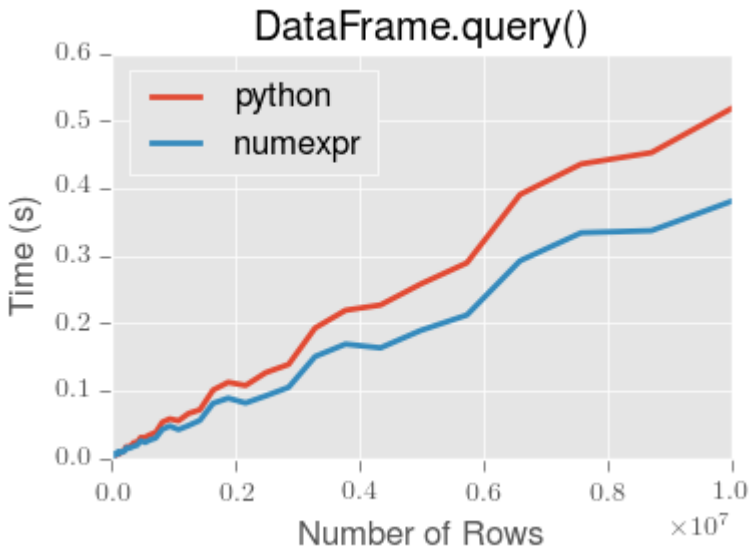
In [278]: shorter
Out[278]:
          a         b         c  bools
7  0.275396  0.691034  0.826619  False

In [279]: longer
Out[279]:
          a         b         c  bools
7  0.275396  0.691034  0.826619  False

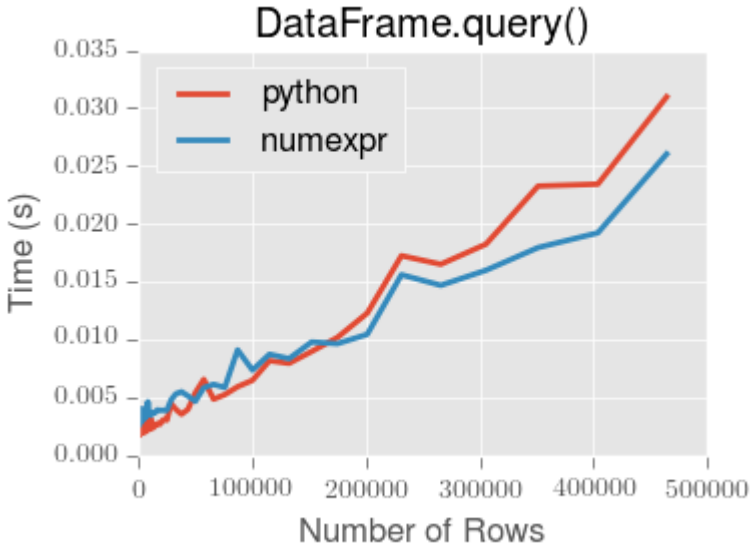
In [280]: shorter == longer
Out[280]:
      a     b     c  bools
7  True  True  True   True
```

Performance of `query()`

`DataFrame.query()` using `numexpr` is slightly faster than Python for large frames.



Note: You will only see the performance benefits of using the `numexpr` engine with `DataFrame.query()` if your frame has more than approximately 200,000 rows.



This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

2.5.18 Duplicate data

If you want to identify and remove duplicate rows in a DataFrame, there are two methods that will help: `duplicated` and `drop_duplicates`. Each takes as an argument the columns to use to identify duplicated rows.

- `duplicated` returns a boolean vector whose length is the number of rows, and which indicates whether a row is duplicated.
- `drop_duplicates` removes duplicate rows.

By default, the first observed row of a duplicate set is considered unique, but each method has a `keep` parameter to specify targets to be kept.

- `keep='first'` (default): mark / drop duplicates except for the first occurrence.
- `keep='last'`: mark / drop duplicates except for the last occurrence.
- `keep=False`: mark / drop all duplicates.

```
In [281]: df2 = pd.DataFrame({'a': ['one', 'one', 'two', 'two', 'two', 'three', 'four
↪'],
   .....:                     'b': ['x', 'y', 'x', 'y', 'x', 'x', 'x'],
   .....:                     'c': np.random.randn(7)})
   .....:

In [282]: df2
Out[282]:
       a  b         c
0    one  x -1.067137
```

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```
1    one  y  0.309500
2    two  x -0.211056
3    two  y -1.842023
4    two  x -0.390820
5  three  x -1.964475
6   four  x  1.298329

In [283]: df2.duplicated('a')
Out[283]:
0    False
1     True
2    False
3     True
4     True
5    False
6    False
dtype: bool

In [284]: df2.duplicated('a', keep='last')
Out[284]:
0     True
1    False
2     True
3     True
4    False
5    False
6    False
dtype: bool

In [285]: df2.duplicated('a', keep=False)
Out[285]:
0     True
1     True
2     True
3     True
4     True
5    False
6    False
dtype: bool

In [286]: df2.drop_duplicates('a')
Out[286]:
       a  b         c
0    one  x -1.067137
2    two  x -0.211056
5  three  x -1.964475
6   four  x  1.298329

In [287]: df2.drop_duplicates('a', keep='last')
Out[287]:
       a  b         c
1    one  y  0.309500
4    two  x -0.390820
5  three  x -1.964475
6   four  x  1.298329

In [288]: df2.drop_duplicates('a', keep=False)
```

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```
Out[288]:
       a  b         c
5  three  x -1.964475
6   four  x  1.298329
```

Also, you can pass a list of columns to identify duplications.

```
In [289]: df2.duplicated(['a', 'b'])
Out[289]:
0    False
1    False
2    False
3    False
4     True
5    False
6    False
dtype: bool

In [290]: df2.drop_duplicates(['a', 'b'])
Out[290]:
       a  b         c
0    one  x -1.067137
1    one  y  0.309500
2    two  x -0.211056
3    two  y -1.842023
5  three  x -1.964475
6   four  x  1.298329
```

To drop duplicates by index value, use `Index.duplicated` then perform slicing. The same set of options are available for the `keep` parameter.

```
In [291]: df3 = pd.DataFrame({'a': np.arange(6),
   .....:                     'b': np.random.randn(6)},
   .....:                    index=['a', 'a', 'b', 'c', 'b', 'a'])
   .....:

In [292]: df3
Out[292]:
   a         b
a  0  1.440455
a  1  2.456086
b  2  1.038402
c  3 -0.894409
b  4  0.683536
a  5  3.082764

In [293]: df3.index.duplicated()
Out[293]: array([False,  True, False, False,  True,  True])

In [294]: df3[~df3.index.duplicated()]
Out[294]:
   a         b
a  0  1.440455
b  2  1.038402
c  3 -0.894409
```

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```
In [295]: df3[~df3.index.duplicated(keep='last')]
Out[295]:
   a         b
c  3 -0.894409
b  4  0.683536
a  5  3.082764

In [296]: df3[~df3.index.duplicated(keep=False)]
Out[296]:
   a         b
c  3 -0.894409
```

2.5.19 Dictionary-like `get()` method

Each of Series or DataFrame have a `get` method which can return a default value.

```
In [297]: s = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [298]: s.get('a')  # equivalent to s['a']
Out[298]: 1

In [299]: s.get('x', default=-1)
Out[299]: -1
```

2.5.20 Looking up values by index/column labels

Sometimes you want to extract a set of values given a sequence of row labels and column labels, this can be achieved by `DataFrame.melt` combined by filtering the corresponding rows with `DataFrame.loc`. For instance:

```
In [300]: df = pd.DataFrame({'col': ["A", "A", "B", "B"],
   .....:                    'A': [80, 23, np.nan, 22],
   .....:                    'B': [80, 55, 76, 67]})
   .....:

In [301]: df
Out[301]:
  col     A   B
0   A  80.0  80
1   A  23.0  55
2   B   NaN  76
3   B  22.0  67

In [302]: melt = df.melt('col')

In [303]: melt = melt.loc[melt['col'] == melt['variable'], 'value']

In [304]: melt.reset_index(drop=True)
Out[304]:
0    80.0
1    23.0
2    76.0
3    67.0
Name: value, dtype: float64
```

Formerly this could be achieved with the dedicated `DataFrame.lookup` method which was deprecated in version 1.2.0.

2.5.21 Index objects

The pandas *Index* class and its subclasses can be viewed as implementing an *ordered multiset*. Duplicates are allowed. However, if you try to convert an *Index* object with duplicate entries into a `set`, an exception will be raised.

Index also provides the infrastructure necessary for lookups, data alignment, and reindexing. The easiest way to create an *Index* directly is to pass a `list` or other sequence to *Index*:

```
In [305]: index = pd.Index(['e', 'd', 'a', 'b'])

In [306]: index
Out[306]: Index(['e', 'd', 'a', 'b'], dtype='object')

In [307]: 'd' in index
Out[307]: True
```

You can also pass a `name` to be stored in the index:

```
In [308]: index = pd.Index(['e', 'd', 'a', 'b'], name='something')

In [309]: index.name
Out[309]: 'something'
```

The name, if set, will be shown in the console display:

```
In [310]: index = pd.Index(list(range(5)), name='rows')

In [311]: columns = pd.Index(['A', 'B', 'C'], name='cols')

In [312]: df = pd.DataFrame(np.random.randn(5, 3), index=index, columns=columns)

In [313]: df
Out[313]:
cols         A         B         C
rows
0     1.295989 -1.051694  1.340429
1    -2.366110  0.428241  0.387275
2     0.433306  0.929548  0.278094
3     2.154730 -0.315628  0.264223
4     1.126818  1.132290 -0.353310

In [314]: df['A']
Out[314]:
rows
0    1.295989
1   -2.366110
2    0.433306
3    2.154730
4    1.126818
Name: A, dtype: float64
```

Setting metadata

Indexes are "mostly immutable", but it is possible to set and change their `name` attribute. You can use the `rename`, `set_names` to set these attributes directly, and they default to returning a copy.

See *Advanced Indexing* for usage of MultiIndexes.

```
In [315]: ind = pd.Index([1, 2, 3])

In [316]: ind.rename("apple")
Out[316]: Int64Index([1, 2, 3], dtype='int64', name='apple')

In [317]: ind
Out[317]: Int64Index([1, 2, 3], dtype='int64')

In [318]: ind.set_names(["apple"], inplace=True)

In [319]: ind.name = "bob"

In [320]: ind
Out[320]: Int64Index([1, 2, 3], dtype='int64', name='bob')
```

`set_names`, `set_levels`, and `set_codes` also take an optional `level` argument

```
In [321]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']], names=['first
↪', 'second'])

In [322]: index
Out[322]:
MultiIndex([(0, 'one'),
            (0, 'two'),
            (1, 'one'),
            (1, 'two'),
            (2, 'one'),
            (2, 'two')],
           names=['first', 'second'])

In [323]: index.levels[1]
Out[323]: Index(['one', 'two'], dtype='object', name='second')

In [324]: index.set_levels(["a", "b"], level=1)
Out[324]:
MultiIndex([(0, 'a'),
            (0, 'b'),
            (1, 'a'),
            (1, 'b'),
            (2, 'a'),
            (2, 'b')],
           names=['first', 'second'])
```

Set operations on Index objects

The two main operations are `union` and `intersection`. Difference is provided via the `.difference()` method.

```
In [325]: a = pd.Index(['c', 'b', 'a'])

In [326]: b = pd.Index(['c', 'e', 'd'])

In [327]: a.difference(b)
Out[327]: Index(['a', 'b'], dtype='object')
```

Also available is the `symmetric_difference` operation, which returns elements that appear in either `idx1` or `idx2`, but not in both. This is equivalent to the Index created by `idx1.difference(idx2).union(idx2.difference(idx1))`, with duplicates dropped.

```
In [328]: idx1 = pd.Index([1, 2, 3, 4])

In [329]: idx2 = pd.Index([2, 3, 4, 5])

In [330]: idx1.symmetric_difference(idx2)
Out[330]: Int64Index([1, 5], dtype='int64')
```

Note: The resulting index from a set operation will be sorted in ascending order.

When performing *`Index.union()`* between indexes with different dtypes, the indexes must be cast to a common dtype. Typically, though not always, this is object dtype. The exception is when performing a union between integer and float data. In this case, the integer values are converted to float

```
In [331]: idx1 = pd.Index([0, 1, 2])

In [332]: idx2 = pd.Index([0.5, 1.5])

In [333]: idx1.union(idx2)
Out[333]: Float64Index([0.0, 0.5, 1.0, 1.5, 2.0], dtype='float64')
```

Missing values

Important: Even though `Index` can hold missing values (`NaN`), it should be avoided if you do not want any unexpected results. For example, some operations exclude missing values implicitly.

`Index.fillna` fills missing values with specified scalar value.

```
In [334]: idx1 = pd.Index([1, np.nan, 3, 4])

In [335]: idx1
Out[335]: Float64Index([1.0, nan, 3.0, 4.0], dtype='float64')

In [336]: idx1.fillna(2)
Out[336]: Float64Index([1.0, 2.0, 3.0, 4.0], dtype='float64')

In [337]: idx2 = pd.DatetimeIndex([pd.Timestamp('2011-01-01'),
```

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```
   .....:                          pd.NaT,
   .....:                          pd.Timestamp('2011-01-03')])
   .....:

In [338]: idx2
Out[338]: DatetimeIndex(['2011-01-01', 'NaT', '2011-01-03'], dtype='datetime64[ns]',␣
↪freq=None)

In [339]: idx2.fillna(pd.Timestamp('2011-01-02'))
Out[339]: DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'], dtype=
↪'datetime64[ns]', freq=None)
```

2.5.22 Set / reset index

Occasionally you will load or create a data set into a DataFrame and want to add an index after you've already done so. There are a couple of different ways.

Set an index

DataFrame has a *set_index()* method which takes a column name (for a regular `Index`) or a list of column names (for a `MultiIndex`). To create a new, re-indexed DataFrame:

```
In [340]: data
Out[340]:
     a    b  c    d
0  bar  one  z  1.0
1  bar  two  y  2.0
2  foo  one  x  3.0
3  foo  two  w  4.0

In [341]: indexed1 = data.set_index('c')

In [342]: indexed1
Out[342]:
     a    b    d
c
z  bar  one  1.0
y  bar  two  2.0
x  foo  one  3.0
w  foo  two  4.0

In [343]: indexed2 = data.set_index(['a', 'b'])

In [344]: indexed2
Out[344]:
         c    d
a   b
bar one  z  1.0
    two  y  2.0
foo one  x  3.0
    two  w  4.0
```

The `append` keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

```
In [345]: frame = data.set_index('c', drop=False)

In [346]: frame = frame.set_index(['a', 'b'], append=True)

In [347]: frame
Out[347]:
            c    d
c a   b
z bar one   z  1.0
y bar two   y  2.0
x foo one   x  3.0
w foo two   w  4.0
```

Other options in `set_index` allow you not drop the index columns or to add the index in-place (without creating a new object):

```
In [348]: data.set_index('c', drop=False)
Out[348]:
     a    b  c    d
c
z  bar  one  z  1.0
y  bar  two  y  2.0
x  foo  one  x  3.0
w  foo  two  w  4.0

In [349]: data.set_index(['a', 'b'], inplace=True)

In [350]: data
Out[350]:
          c    d
a   b
bar one   z  1.0
    two   y  2.0
foo one   x  3.0
    two   w  4.0
```

Reset the index

As a convenience, there is a new function on DataFrame called *reset_index()* which transfers the index values into the DataFrame's columns and sets a simple integer index. This is the inverse operation of *set_index()*.

```
In [351]: data
Out[351]:
          c    d
a   b
bar one   z  1.0
    two   y  2.0
foo one   x  3.0
    two   w  4.0

In [352]: data.reset_index()
Out[352]:
     a    b  c    d
0  bar  one  z  1.0
1  bar  two  y  2.0
```

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```
2  foo  one  x  3.0
3  foo  two  w  4.0
```

The output is more similar to a SQL table or a record array. The names for the columns derived from the index are the ones stored in the `names` attribute.

You can use the `level` keyword to remove only a portion of the index:

```
In [353]: frame
Out[353]:
           c    d
c a   b
z bar one  z  1.0
y bar two  y  2.0
x foo one  x  3.0
w foo two  w  4.0

In [354]: frame.reset_index(level=1)
Out[354]:
         a  c    d
c b
z one  bar  z  1.0
y two  bar  y  2.0
x one  foo  x  3.0
w two  foo  w  4.0
```

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame's columns.

Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```
data.index = index
```

2.5.23 Returning a view versus a copy

When setting values in a pandas object, care must be taken to avoid what is called `chained indexing`. Here is an example.

```
In [355]: dfmi = pd.DataFrame([list('abcd'),
   .....:                      list('efgh'),
   .....:                      list('ijkl'),
   .....:                      list('mnop')],
   .....:                     columns=pd.MultiIndex.from_product([['one', 'two'],
   .....:                                                         ['first', 'second
↪']]))
   .....:

In [356]: dfmi
Out[356]:
    one          two
  first second first second
0     a      b     c      d
```

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```
1     e     f     g     h
2     i     j     k     l
3     m     n     o     p
```

Compare these two access methods:

```
In [357]: dfmi['one']['second']
Out[357]:
0    b
1    f
2    j
3    n
Name: second, dtype: object
```

```
In [358]: dfmi.loc[:, ('one', 'second')]
Out[358]:
0    b
1    f
2    j
3    n
Name: (one, second), dtype: object
```

These both yield the same results, so which should you use? It is instructive to understand the order of operations on these and why method 2 (`.loc`) is much preferred over method 1 (chained `[]`).

`dfmi['one']` selects the first level of the columns and returns a DataFrame that is singly-indexed. Then another Python operation `dfmi_with_one['second']` selects the series indexed by `'second'`. This is indicated by the variable `dfmi_with_one` because pandas sees these operations as separate events. e.g. separate calls to `__getitem__`, so it has to treat them as linear operations, they happen one after another.

Contrast this to `df.loc[:,('one','second')]` which passes a nested tuple of `(slice(None),('one', 'second'))` to a single call to `__getitem__`. This allows pandas to deal with this as a single entity. Furthermore this order of operations *can* be significantly faster, and allows one to index *both* axes if so desired.

Why does assignment fail when using chained indexing?

The problem in the previous section is just a performance issue. What's up with the `SettingWithCopy` warning? We don't **usually** throw warnings around when you do something that might cost a few extra milliseconds!

But it turns out that assigning to the product of chained indexing has inherently unpredictable results. To see this, think about how the Python interpreter executes this code:

```
dfmi.loc[:, ('one', 'second')] = value
# becomes
dfmi.loc.__setitem__((slice(None), ('one', 'second')), value)
```

But this code is handled differently:

```
dfmi['one']['second'] = value
# becomes
dfmi.__getitem__('one').__setitem__('second', value)
```

See that `__getitem__` in there? Outside of simple cases, it's very hard to predict whether it will return a view or a copy (it depends on the memory layout of the array, about which pandas makes no guarantees), and therefore whether the `__setitem__` will modify `dfmi` or a temporary object that gets thrown out immediately afterward. **That's** what `SettingWithCopy` is warning you about!

Note: You may be wondering whether we should be concerned about the `loc` property in the first example. But `dfmi.loc` is guaranteed to be `dfmi` itself with modified indexing behavior, so `dfmi.loc.__getitem__` / `dfmi.loc.__setitem__` operate on `dfmi` directly. Of course, `dfmi.loc.__getitem__(idx)` may be a view or a copy of `dfmi`.

Sometimes a `SettingWithCopy` warning will arise at times when there's no obvious chained indexing going on. **These** are the bugs that `SettingWithCopy` is designed to catch! pandas is probably trying to warn you that you've done this:

```
def do_something(df):
    foo = df[['bar', 'baz']]  # Is foo a view? A copy? Nobody knows!
    # ... many lines here ...
    # We don't know whether this will modify df or not!
    foo['quux'] = value
    return foo
```

Yikes!

Evaluation order matters

When you use chained indexing, the order and type of the indexing operation partially determine whether the result is a slice into the original object, or a copy of the slice.

pandas has the `SettingWithCopyWarning` because assigning to a copy of a slice is frequently not intentional, but a mistake caused by chained indexing returning a copy where a slice was expected.

If you would like pandas to be more or less trusting about assignment to a chained indexing expression, you can set the *option* `mode.chained_assignment` to one of these values:

- `'warn'`, the default, means a `SettingWithCopyWarning` is printed.
- `'raise'` means pandas will raise a `SettingWithCopyException` you have to deal with.
- `None` will suppress the warnings entirely.

```
In [359]: dfb = pd.DataFrame({'a': ['one', 'one', 'two',
   .....:                           'three', 'two', 'one', 'six'],
   .....:                   'c': np.arange(7)})
   .....:

# This will show the SettingWithCopyWarning
# but the frame values will be set
In [360]: dfb['c'][dfb['a'].str.startswith('o')] = 42
```

This however is operating on a copy and will not work.

```
>>> pd.set_option('mode.chained_assignment','warn')
>>> dfb[dfb['a'].str.startswith('o')]['c'] = 42
Traceback (most recent call last)
     ...
SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_index,col_indexer] = value instead
```

A chained assignment can also crop up in setting in a mixed dtype frame.

Note: These setting rules apply to all of `.loc/.iloc`.

The following is the recommended access method using `.loc` for multiple items (using `mask`) and a single item using a fixed index:

```
In [361]: dfc = pd.DataFrame({'a': ['one', 'one', 'two',
   .....:                           'three', 'two', 'one', 'six'],
   .....:                    'c': np.arange(7)})
   .....:

In [362]: dfd = dfc.copy()

# Setting multiple items using a mask
In [363]: mask = dfd['a'].str.startswith('o')

In [364]: dfd.loc[mask, 'c'] = 42

In [365]: dfd
Out[365]:
       a   c
0    one  42
1    one  42
2    two   2
3  three   3
4    two   4
5    one  42
6    six   6

# Setting a single item
In [366]: dfd = dfc.copy()

In [367]: dfd.loc[2, 'a'] = 11

In [368]: dfd
Out[368]:
       a  c
0    one  0
1    one  1
2     11  2
3  three  3
4    two  4
5    one  5
6    six  6
```

The following *can* work at times, but it is not guaranteed to, and therefore should be avoided:

```
In [369]: dfd = dfc.copy()

In [370]: dfd['a'][2] = 111

In [371]: dfd
Out[371]:
       a  c
0    one  0
1    one  1
2    111  2
```

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```
3  three  3
4    two  4
5    one  5
6    six  6
```

Last, the subsequent example will **not** work at all, and so should be avoided:

```
>>> pd.set_option('mode.chained_assignment','raise')
>>> dfd.loc[0]['a'] = 1111
Traceback (most recent call last)
     ...
SettingWithCopyException:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_index,col_indexer] = value instead
```

Warning: The chained assignment warnings / exceptions are aiming to inform the user of a possibly invalid assignment. There may be false positives; situations where a chained assignment is inadvertently reported.

2.6 MultiIndex / advanced indexing

This section covers *indexing with a MultiIndex* and *other advanced indexing features*.

See the *Indexing and Selecting Data* for general indexing documentation.

Warning: Whether a copy or a reference is returned for a setting operation may depend on the context. This is sometimes called `chained assignment` and should be avoided. See *Returning a View versus Copy*.

See the *cookbook* for some advanced strategies.

2.6.1 Hierarchical indexing (MultiIndex)

Hierarchical / Multi-level indexing is very exciting as it opens the door to some quite sophisticated data analysis and manipulation, especially for working with higher dimensional data. In essence, it enables you to store and manipulate data with an arbitrary number of dimensions in lower dimensional data structures like `Series` (1d) and `DataFrame` (2d).

In this section, we will show what exactly we mean by "hierarchical" indexing and how it integrates with all of the pandas indexing functionality described above and in prior sections. Later, when discussing *group by* and *pivoting and reshaping data*, we'll show non-trivial applications to illustrate how it aids in structuring data for analysis.

See the *cookbook* for some advanced strategies.

Changed in version 0.24.0: `MultiIndex.labels` has been renamed to *`MultiIndex.codes`* and `MultiIndex.set_labels` to *`MultiIndex.set_codes`*.

Creating a MultiIndex (hierarchical index) object

The *MultiIndex* object is the hierarchical analogue of the standard *Index* object which typically stores the axis labels in pandas objects. You can think of MultiIndex as an array of tuples where each tuple is unique. A MultiIndex can be created from a list of arrays (using *MultiIndex.from_arrays()*), an array of tuples (using *MultiIndex.from_tuples()*), a crossed set of iterables (using *MultiIndex.from_product()*), or a *DataFrame* (using *MultiIndex.from_frame()*). The Index constructor will attempt to return a MultiIndex when it is passed a list of tuples. The following examples demonstrate different ways to initialize MultiIndexes.

```
In [1]: arrays = [
   ...:     ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
   ...:     ["one", "two", "one", "two", "one", "two", "one", "two"],
   ...: ]
   ...:

In [2]: tuples = list(zip(*arrays))

In [3]: tuples
Out[3]:
[('bar', 'one'),
 ('bar', 'two'),
 ('baz', 'one'),
 ('baz', 'two'),
 ('foo', 'one'),
 ('foo', 'two'),
 ('qux', 'one'),
 ('qux', 'two')]

In [4]: index = pd.MultiIndex.from_tuples(tuples, names=["first", "second"])

In [5]: index
Out[5]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two'),
            ('qux', 'one'),
            ('qux', 'two')],
           names=['first', 'second'])

In [6]: s = pd.Series(np.random.randn(8), index=index)

In [7]: s
Out[7]:
first  second
bar    one       0.469112
       two      -0.282863
baz    one      -1.509059
       two      -1.135632
foo    one       1.212112
       two      -0.173215
qux    one       0.119209
       two      -1.044236
dtype: float64
```

When you want every pairing of the elements in two iterables, it can be easier to use the *MultiIndex.from_product()* method:

```
In [8]: iterables = [["bar", "baz", "foo", "qux"], ["one", "two"]]

In [9]: pd.MultiIndex.from_product(iterables, names=["first", "second"])
Out[9]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two'),
            ('qux', 'one'),
            ('qux', 'two')],
           names=['first', 'second'])
```

You can also construct a `MultiIndex` from a `DataFrame` directly, using the method *MultiIndex.from_frame()*. This is a complementary method to *MultiIndex.to_frame()*.

New in version 0.24.0.

```
In [10]: df = pd.DataFrame(
   ....:     [["bar", "one"], ["bar", "two"], ["foo", "one"], ["foo", "two"]],
   ....:     columns=["first", "second"],
   ....: )
   ....:

In [11]: pd.MultiIndex.from_frame(df)
Out[11]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('foo', 'one'),
            ('foo', 'two')],
           names=['first', 'second'])
```

As a convenience, you can pass a list of arrays directly into `Series` or `DataFrame` to construct a `MultiIndex` automatically:

```
In [12]: arrays = [
   ....:     np.array(["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"]),
   ....:     np.array(["one", "two", "one", "two", "one", "two", "one", "two"]),
   ....: ]
   ....:

In [13]: s = pd.Series(np.random.randn(8), index=arrays)

In [14]: s
Out[14]:
bar  one   -0.861849
     two   -2.104569
baz  one   -0.494929
     two    1.071804
foo  one    0.721555
     two   -0.706771
qux  one   -1.039575
     two    0.271860
dtype: float64
```

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```
In [15]: df = pd.DataFrame(np.random.randn(8, 4), index=arrays)

In [16]: df
Out[16]:
                0         1         2         3
bar one -0.424972  0.567020  0.276232 -1.087401
    two -0.673690  0.113648 -1.478427  0.524988
baz one  0.404705  0.577046 -1.715002 -1.039268
    two -0.370647 -1.157892 -1.344312  0.844885
foo one  1.075770 -0.109050  1.643563 -1.469388
    two  0.357021 -0.674600 -1.776904 -0.968914
qux one -1.294524  0.413738  0.276662 -0.472035
    two -0.013960 -0.362543 -0.006154 -0.923061
```

All of the `MultiIndex` constructors accept a `names` argument which stores string names for the levels themselves. If no names are provided, `None` will be assigned:

```
In [17]: df.index.names
Out[17]: FrozenList([None, None])
```

This index can back any axis of a pandas object, and the number of **levels** of the index is up to you:

```
In [18]: df = pd.DataFrame(np.random.randn(3, 8), index=["A", "B", "C"],␣
↪columns=index)

In [19]: df
Out[19]:
first        bar                 baz                 foo                 qux
second       one       two       one       two       one       two       one       two
A       0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.170299 -0.226169
B       0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127 -1.436737
C      -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747

In [20]: pd.DataFrame(np.random.randn(6, 6), index=index[:6], columns=index[:6])
Out[20]:
first              bar                 baz                 foo
second             one       two       one       two       one       two
first second
bar   one    -0.410001 -0.078638  0.545952 -1.219217 -1.226825  0.769804
      two    -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734
baz   one     0.959726 -1.110336 -0.619976  0.149748 -0.732339  0.687738
      two     0.176444  0.403310 -0.154951  0.301624 -2.179861 -1.369849
foo   one    -0.954208  1.462696 -1.743161 -0.826591 -0.345352  1.314232
      two     0.690579  0.995761  2.396780  0.014871  3.357427 -0.317441
```

We've "sparsified" the higher levels of the indexes to make the console output a bit easier on the eyes. Note that how the index is displayed can be controlled using the `multi_sparse` option in `pandas.set_options()`:

```
In [21]: with pd.option_context("display.multi_sparse", False):
   ....:     df
   ....:
```

It's worth keeping in mind that there's nothing preventing you from using tuples as atomic labels on an axis:

```
In [22]: pd.Series(np.random.randn(8), index=tuples)
Out[22]:
(bar, one)   -1.236269
(bar, two)    0.896171
(baz, one)   -0.487602
(baz, two)   -0.082240
(foo, one)   -2.182937
(foo, two)    0.380396
(qux, one)    0.084844
(qux, two)    0.432390
dtype: float64
```

The reason that the `MultiIndex` matters is that it can allow you to do grouping, selection, and reshaping operations as we will describe below and in subsequent areas of the documentation. As you will see in later sections, you can find yourself working with hierarchically-indexed data without creating a `MultiIndex` explicitly yourself. However, when loading data from a file, you may wish to generate your own `MultiIndex` when preparing the data set.

Reconstructing the level labels

The method *`get_level_values()`* will return a vector of the labels for each location at a particular level:

```
In [23]: index.get_level_values(0)
Out[23]: Index(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'], dtype='object
↪', name='first')

In [24]: index.get_level_values("second")
Out[24]: Index(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'], dtype='object
↪', name='second')
```

Basic indexing on axis with MultiIndex

One of the important features of hierarchical indexing is that you can select data by a "partial" label identifying a subgroup in the data. **Partial** selection "drops" levels of the hierarchical index in the result in a completely analogous way to selecting a column in a regular DataFrame:

```
In [25]: df["bar"]
Out[25]:
second       one       two
A       0.895717  0.805244
B       0.410835  0.813850
C      -1.413681  1.607920

In [26]: df["bar", "one"]
Out[26]:
A    0.895717
B    0.410835
C   -1.413681
Name: (bar, one), dtype: float64

In [27]: df["bar"]["one"]
Out[27]:
A    0.895717
B    0.410835
C   -1.413681
```

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```
Name: one, dtype: float64

In [28]: s["qux"]
Out[28]:
one   -1.039575
two    0.271860
dtype: float64
```

See *Cross-section with hierarchical index* for how to select on a deeper level.

Defined levels

The `MultiIndex` keeps all the defined levels of an index, even if they are not actually used. When slicing an index, you may notice this. For example:

```
In [29]: df.columns.levels  # original MultiIndex
Out[29]: FrozenList([['bar', 'baz', 'foo', 'qux'], ['one', 'two']])

In [30]: df[["foo","qux"]].columns.levels  # sliced
Out[30]: FrozenList([['bar', 'baz', 'foo', 'qux'], ['one', 'two']])
```

This is done to avoid a recomputation of the levels in order to make slicing highly performant. If you want to see only the used levels, you can use the `get_level_values()` method.

```
In [31]: df[["foo", "qux"]].columns.to_numpy()
Out[31]:
array([('foo', 'one'), ('foo', 'two'), ('qux', 'one'), ('qux', 'two')],
      dtype=object)

# for a specific level
In [32]: df[["foo", "qux"]].columns.get_level_values(0)
Out[32]: Index(['foo', 'foo', 'qux', 'qux'], dtype='object', name='first')
```

To reconstruct the `MultiIndex` with only the used levels, the `remove_unused_levels()` method may be used.

```
In [33]: new_mi = df[["foo", "qux"]].columns.remove_unused_levels()

In [34]: new_mi.levels
Out[34]: FrozenList([['foo', 'qux'], ['one', 'two']])
```

Data alignment and using `reindex`

Operations between differently-indexed objects having `MultiIndex` on the axes will work as you expect; data alignment will work the same as an Index of tuples:

```
In [35]: s + s[:-2]
Out[35]:
bar  one   -1.723698
     two   -4.209138
baz  one   -0.989859
     two    2.143608
foo  one    1.443110
     two   -1.413542
qux  one         NaN
```

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```
     two         NaN
dtype: float64

In [36]: s + s[::2]
Out[36]:
bar  one   -1.723698
     two         NaN
baz  one   -0.989859
     two         NaN
foo  one    1.443110
     two         NaN
qux  one   -2.079150
     two         NaN
dtype: float64
```

The *reindex()* method of Series/DataFrames can be called with another MultiIndex, or even a list or array of tuples:

```
In [37]: s.reindex(index[:3])
Out[37]:
first  second
bar    one      -0.861849
       two      -2.104569
baz    one      -0.494929
dtype: float64

In [38]: s.reindex([("foo", "two"), ("bar", "one"), ("qux", "one"), ("baz", "one")])
Out[38]:
foo  two   -0.706771
bar  one   -0.861849
qux  one   -1.039575
baz  one   -0.494929
dtype: float64
```

2.6.2 Advanced indexing with hierarchical index

Syntactically integrating MultiIndex in advanced indexing with .loc is a bit challenging, but we've made every effort to do so. In general, MultiIndex keys take the form of tuples. For example, the following works as you would expect:

```
In [39]: df = df.T

In [40]: df
Out[40]:
                     A         B         C
first second
bar   one     0.895717  0.410835 -1.413681
      two     0.805244  0.813850  1.607920
baz   one    -1.206412  0.132003  1.024180
      two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
qux   one    -1.170299  1.130127  0.974466
      two    -0.226169 -1.436737 -2.006747
```

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```
In [41]: df.loc[("bar", "two")]
Out[41]:
A    0.805244
B    0.813850
C    1.607920
Name: (bar, two), dtype: float64
```

Note that `df.loc['bar', 'two']` would also work in this example, but this shorthand notation can lead to ambiguity in general.

If you also want to index a specific column with `.loc`, you must use a tuple like this:

```
In [42]: df.loc[("bar", "two"), "A"]
Out[42]: 0.8052440253863785
```

You don't have to specify all levels of the `MultiIndex` by passing only the first elements of the tuple. For example, you can use "partial" indexing to get all elements with `bar` in the first level as follows:

```
In [43]: df.loc["bar"]
Out[43]:
               A         B         C
second
one     0.895717  0.410835 -1.413681
two     0.805244  0.813850  1.607920
```

This is a shortcut for the slightly more verbose notation `df.loc[('bar',),]` (equivalent to `df.loc['bar',]` in this example).

"Partial" slicing also works quite nicely.

```
In [44]: df.loc["baz":"foo"]
Out[44]:
                     A         B         C
first second
baz   one    -1.206412  0.132003  1.024180
      two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
```

You can slice with a 'range' of values, by providing a slice of tuples.

```
In [45]: df.loc[("baz", "two"):("qux", "one")]
Out[45]:
                     A         B         C
first second
baz   two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
qux   one    -1.170299  1.130127  0.974466

In [46]: df.loc[("baz", "two"):"foo"]
Out[46]:
                     A         B         C
first second
baz   two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
```

Passing a list of labels or tuples works similar to reindexing:

```
In [47]: df.loc[[("bar", "two"), ("qux", "one")]]
Out[47]:
                     A         B         C
first second
bar   two      0.805244  0.813850  1.607920
qux   one     -1.170299  1.130127  0.974466
```

Note: It is important to note that tuples and lists are not treated identically in pandas when it comes to indexing. Whereas a tuple is interpreted as one multi-level key, a list is used to specify several keys. Or in other words, tuples go horizontally (traversing levels), lists go vertically (scanning levels).

Importantly, a list of tuples indexes several complete `MultiIndex` keys, whereas a tuple of lists refer to several values within a level:

```
In [48]: s = pd.Series(
   ....:     [1, 2, 3, 4, 5, 6],
   ....:     index=pd.MultiIndex.from_product([["A", "B"], ["c", "d", "e"]]),
   ....: )
   ....:

In [49]: s.loc[[("A", "c"), ("B", "d")]]  # list of tuples
Out[49]:
A  c    1
B  d    5
dtype: int64

In [50]: s.loc[(["A", "B"], ["c", "d"])]  # tuple of lists
Out[50]:
A  c    1
   d    2
B  c    4
   d    5
dtype: int64
```

Using slicers

You can slice a `MultiIndex` by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see *Selection by Label*, including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of *that* level. You do not need to specify all the *deeper* levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

Warning: You should specify all axes in the `.loc` specifier, meaning the indexer for the **index** and for the **columns**. There are some ambiguous cases where the passed indexer could be mis-interpreted as indexing *both* axes, rather than into say the `MultiIndex` for the rows.

You should do this:

```
df.loc[(slice("A1", "A3"), ...), :]  # noqa: E999
```

You should **not** do this:

```
df.loc[(slice("A1", "A3"), ...)]  # noqa: E999
```

```
In [51]: def mklbl(prefix, n):
   ....:     return ["%s%s" % (prefix, i) for i in range(n)]
   ....:

In [52]: miindex = pd.MultiIndex.from_product(
   ....:     [mklbl("A", 4), mklbl("B", 2), mklbl("C", 4), mklbl("D", 2)]
   ....: )
   ....:

In [53]: micolumns = pd.MultiIndex.from_tuples(
   ....:     [("a", "foo"), ("a", "bar"), ("b", "foo"), ("b", "bah")], names=["lvl0",
↪"lvl1"]
   ....: )
   ....:

In [54]: dfmi = (
   ....:     pd.DataFrame(
   ....:         np.arange(len(miindex) * len(micolumns)).reshape(
   ....:             (len(miindex), len(micolumns))
   ....:         ),
   ....:         index=miindex,
   ....:         columns=micolumns,
   ....:     )
   ....:     .sort_index()
   ....:     .sort_index(axis=1)
   ....: )
   ....:

In [55]: dfmi
Out[55]:
lvl0            a         b
lvl1          bar  foo  bah  foo
A0 B0 C0 D0     1    0    3    2
         D1     5    4    7    6
      C1 D0     9    8   11   10
         D1    13   12   15   14
      C2 D0    17   16   19   18
...           ...  ...  ...  ...
A3 B1 C1 D1   237  236  239  238
      C2 D0   241  240  243  242
         D1   245  244  247  246
      C3 D0   249  248  251  250
         D1   253  252  255  254

[64 rows x 4 columns]
```

Basic MultiIndex slicing using slices, lists, and labels.

```
In [56]: dfmi.loc[(slice("A1", "A3"), slice(None), ["C1", "C3"]), :]
Out[56]:
lvl0            a         b
lvl1          bar  foo  bah  foo
```

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```
A1 B0 C1 D0   73   72   75   74
         D1   77   76   79   78
      C3 D0   89   88   91   90
         D1   93   92   95   94
   B1 C1 D0  105  104  107  106
...           ...  ...  ...  ...
A3 B0 C3 D1  221  220  223  222
   B1 C1 D0  233  232  235  234
         D1  237  236  239  238
      C3 D0  249  248  251  250
         D1  253  252  255  254

[24 rows x 4 columns]
```

You can use *pandas.IndexSlice* to facilitate a more natural syntax using `:`, rather than using `slice(None)`.

```
In [57]: idx = pd.IndexSlice

In [58]: dfmi.loc[idx[:, :, ["C1", "C3"]], idx[:, "foo"]]
Out[58]:
lvl0           a    b
lvl1         foo  foo
A0 B0 C1 D0    8   10
         D1   12   14
      C3 D0   24   26
         D1   28   30
   B1 C1 D0   40   42
...           ...  ...
A3 B0 C3 D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254

[32 rows x 2 columns]
```

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```
In [59]: dfmi.loc["A1", (slice(None), "foo")]
Out[59]:
lvl0        a    b
lvl1      foo  foo
B0 C0 D0   64   66
      D1   68   70
   C1 D0   72   74
      D1   76   78
   C2 D0   80   82
...       ...  ...
B1 C1 D1  108  110
   C2 D0  112  114
      D1  116  118
   C3 D0  120  122
      D1  124  126

[16 rows x 2 columns]

In [60]: dfmi.loc[idx[:, :, ["C1", "C3"]], idx[:, "foo"]]
```

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```
Out[60]:
lvl0           a    b
lvl1         foo  foo
A0 B0 C1 D0    8   10
         D1   12   14
      C3 D0   24   26
         D1   28   30
   B1 C1 D0   40   42
...          ...  ...
A3 B0 C3 D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254

[32 rows x 2 columns]
```

Using a boolean indexer you can provide selection related to the *values*.

```
In [61]: mask = dfmi[("a", "foo")] > 200

In [62]: dfmi.loc[idx[mask, :, ["C1", "C3"]], idx[:, "foo"]]
Out[62]:
lvl0           a    b
lvl1         foo  foo
A3 B0 C1 D1  204  206
      C3 D0  216  218
         D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254
```

You can also specify the `axis` argument to `.loc` to interpret the passed slicers on a single axis.

```
In [63]: dfmi.loc(axis=0)[:, :, ["C1", "C3"]]
Out[63]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C1 D0    9    8   11   10
         D1   13   12   15   14
      C3 D0   25   24   27   26
         D1   29   28   31   30
   B1 C1 D0   41   40   43   42
...          ...  ...  ...  ...
A3 B0 C3 D1  221  220  223  222
   B1 C1 D0  233  232  235  234
         D1  237  236  239  238
      C3 D0  249  248  251  250
         D1  253  252  255  254

[32 rows x 4 columns]
```

Furthermore, you can *set* the values using the following methods.

```
In [64]: df2 = dfmi.copy()
```

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```
In [65]: df2.loc(axis=0)[:, :, ["C1", "C3"]] = -10

In [66]: df2
Out[66]:
lvl0            a         b
lvl1          bar  foo  bah  foo
A0 B0 C0 D0     1    0    3    2
         D1     5    4    7    6
      C1 D0   -10  -10  -10  -10
         D1   -10  -10  -10  -10
      C2 D0    17   16   19   18
...           ...  ...  ...  ...
A3 B1 C1 D1   -10  -10  -10  -10
      C2 D0   241  240  243  242
         D1   245  244  247  246
      C3 D0   -10  -10  -10  -10
         D1   -10  -10  -10  -10

[64 rows x 4 columns]
```

You can use a right-hand-side of an alignable object as well.

```
In [67]: df2 = dfmi.copy()

In [68]: df2.loc[idx[:, :, ["C1", "C3"]], :] = df2 * 1000

In [69]: df2
Out[69]:
lvl0              a                b
lvl1            bar     foo     bah     foo
A0 B0 C0 D0       1       0       3       2
         D1       5       4       7       6
      C1 D0    9000    8000   11000   10000
         D1   13000   12000   15000   14000
      C2 D0      17      16      19      18
...             ...     ...     ...     ...
A3 B1 C1 D1  237000  236000  239000  238000
      C2 D0     241     240     243     242
         D1     245     244     247     246
      C3 D0  249000  248000  251000  250000
         D1  253000  252000  255000  254000

[64 rows x 4 columns]
```

Cross-section

The `xs()` method of `DataFrame` additionally takes a level argument to make selecting data at a particular level of a `MultiIndex` easier.

```
In [70]: df
Out[70]:
                     A         B         C
first second
bar   one     0.895717  0.410835 -1.413681
      two     0.805244  0.813850  1.607920
```

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```
baz   one    -1.206412  0.132003  1.024180
      two     2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
      two     1.340309 -1.187678 -2.211372
qux   one    -1.170299  1.130127  0.974466
      two    -0.226169 -1.436737 -2.006747

In [71]: df.xs("one", level="second")
Out[71]:
              A         B         C
first
bar    0.895717  0.410835 -1.413681
baz   -1.206412  0.132003  1.024180
foo    1.431256 -0.076467  0.875906
qux   -1.170299  1.130127  0.974466
```

```
# using the slicers
In [72]: df.loc[(slice(None), "one"), :]
Out[72]:
                     A         B         C
first second
bar   one     0.895717  0.410835 -1.413681
baz   one    -1.206412  0.132003  1.024180
foo   one     1.431256 -0.076467  0.875906
qux   one    -1.170299  1.130127  0.974466
```

You can also select on the columns with `xs`, by providing the axis argument.

```
In [73]: df = df.T

In [74]: df.xs("one", level="second", axis=1)
Out[74]:
first       bar       baz       foo       qux
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

```
# using the slicers
In [75]: df.loc[:, (slice(None), "one")]
Out[75]:
first        bar       baz       foo       qux
second       one       one       one       one
A       0.895717 -1.206412  1.431256 -1.170299
B       0.410835  0.132003 -0.076467  1.130127
C      -1.413681  1.024180  0.875906  0.974466
```

`xs` also allows selection with multiple keys.

```
In [76]: df.xs(("one", "bar"), level=("second", "first"), axis=1)
Out[76]:
first        bar
second       one
A       0.895717
B       0.410835
C      -1.413681
```

```
# using the slicers
In [77]: df.loc[:, ("bar", "one")]
Out[77]:
A    0.895717
B    0.410835
C   -1.413681
Name: (bar, one), dtype: float64
```

You can pass `drop_level=False` to `xs` to retain the level that was selected.

```
In [78]: df.xs("one", level="second", axis=1, drop_level=False)
Out[78]:
first        bar       baz       foo       qux
second       one       one       one       one
A       0.895717 -1.206412  1.431256 -1.170299
B       0.410835  0.132003 -0.076467  1.130127
C      -1.413681  1.024180  0.875906  0.974466
```

Compare the above with the result using `drop_level=True` (the default value).

```
In [79]: df.xs("one", level="second", axis=1, drop_level=True)
Out[79]:
first       bar       baz       foo       qux
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

Advanced reindexing and alignment

Using the parameter `level` in the *`reindex()`* and *`align()`* methods of pandas objects is useful to broadcast values across a level. For instance:

```
In [80]: midx = pd.MultiIndex(
   ....:     levels=[["zero", "one"], ["x", "y"]], codes=[[1, 1, 0, 0], [1, 0, 1, 0]]
   ....: )
   ....:

In [81]: df = pd.DataFrame(np.random.randn(4, 2), index=midx)

In [82]: df
Out[82]:
                0         1
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520

In [83]: df2 = df.mean(level=0)

In [84]: df2
Out[84]:
              0         1
one    1.060074 -0.109716
zero   1.271532  0.713416

In [85]: df2.reindex(df.index, level=0)
```

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```
Out[85]:
                0         1
one  y  1.060074 -0.109716
     x  1.060074 -0.109716
zero y  1.271532  0.713416
     x  1.271532  0.713416

# aligning
In [86]: df_aligned, df2_aligned = df.align(df2, level=0)

In [87]: df_aligned
Out[87]:
                0         1
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520

In [88]: df2_aligned
Out[88]:
                0         1
one  y  1.060074 -0.109716
     x  1.060074 -0.109716
zero y  1.271532  0.713416
     x  1.271532  0.713416
```

Swapping levels with `swaplevel`

The *`swaplevel()`* method can switch the order of two levels:

```
In [89]: df[:5]
Out[89]:
                0         1
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520

In [90]: df[:5].swaplevel(0, 1, axis=0)
Out[90]:
                0         1
y one   1.519970 -0.493662
x one   0.600178  0.274230
y zero  0.132885 -0.023688
x zero  2.410179  1.450520
```

Reordering levels with `reorder_levels`

The *`reorder_levels()`* method generalizes the `swaplevel` method, allowing you to permute the hierarchical index levels in one step:

```
In [91]: df[:5].reorder_levels([1, 0], axis=0)
Out[91]:
                0         1
y one    1.519970 -0.493662
x one    0.600178  0.274230
y zero   0.132885 -0.023688
x zero   2.410179  1.450520
```

Renaming names of an `Index` or `MultiIndex`

The *`rename()`* method is used to rename the labels of a `MultiIndex`, and is typically used to rename the columns of a `DataFrame`. The `columns` argument of `rename` allows a dictionary to be specified that includes only the columns you wish to rename.

```
In [92]: df.rename(columns={0: "col0", 1: "col1"})
Out[92]:
             col0      col1
one  y   1.519970 -0.493662
     x   0.600178  0.274230
zero y   0.132885 -0.023688
     x   2.410179  1.450520
```

This method can also be used to rename specific labels of the main index of the `DataFrame`.

```
In [93]: df.rename(index={"one": "two", "y": "z"})
Out[93]:
                0         1
two  z   1.519970 -0.493662
     x   0.600178  0.274230
zero z   0.132885 -0.023688
     x   2.410179  1.450520
```

The *`rename_axis()`* method is used to rename the name of a `Index` or `MultiIndex`. In particular, the names of the levels of a `MultiIndex` can be specified, which is useful if `reset_index()` is later used to move the values from the `MultiIndex` to a column.

```
In [94]: df.rename_axis(index=["abc", "def"])
Out[94]:
                  0         1
abc  def
one  y     1.519970 -0.493662
     x     0.600178  0.274230
zero y     0.132885 -0.023688
     x     2.410179  1.450520
```

Note that the columns of a `DataFrame` are an index, so that using `rename_axis` with the `columns` argument will change the name of that index.

```
In [95]: df.rename_axis(columns="Cols").columns
Out[95]: RangeIndex(start=0, stop=2, step=1, name='Cols')
```

Both `rename` and `rename_axis` support specifying a dictionary, `Series` or a mapping function to map labels/names to new values.

When working with an `Index` object directly, rather than via a `DataFrame`, *`Index.set_names()`* can be used to change the names.

```
In [96]: mi = pd.MultiIndex.from_product([[1, 2], ["a", "b"]], names=["x", "y"])

In [97]: mi.names
Out[97]: FrozenList(['x', 'y'])

In [98]: mi2 = mi.rename("new name", level=0)

In [99]: mi2
Out[99]:
MultiIndex([(1, 'a'),
            (1, 'b'),
            (2, 'a'),
            (2, 'b')],
           names=['new name', 'y'])
```

You cannot set the names of the MultiIndex via a level.

```
In [100]: mi.levels[0].name = "name via level"
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
<ipython-input-100-35d32a9a5218> in <module>
----> 1 mi.levels[0].name = "name via level"

/pandas/pandas/core/indexes/base.py in name(self, value)
   1241         if self._no_setting_name:
   1242             # Used in MultiIndex.levels to avoid silently ignoring name␣
 ↪updates.
-> 1243             raise RuntimeError(
   1244                 "Cannot set name on a level of a MultiIndex. Use "
   1245                 "'MultiIndex.set_names' instead."

RuntimeError: Cannot set name on a level of a MultiIndex. Use 'MultiIndex.set_names'␣
 ↪instead.
```

Use *`Index.set_names()`* instead.

2.6.3 Sorting a `MultiIndex`

For *`MultiIndex`*-ed objects to be indexed and sliced effectively, they need to be sorted. As with any index, you can use *`sort_index()`*.

```
In [101]: import random

In [102]: random.shuffle(tuples)

In [103]: s = pd.Series(np.random.randn(8), index=pd.MultiIndex.from_tuples(tuples))

In [104]: s
Out[104]:
bar  two    0.206053
qux  two   -0.251905
```

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```
bar  one   -2.213588
baz  two    1.063327
     one    1.266143
foo  two    0.299368
qux  one   -0.863838
foo  one    0.408204
dtype: float64

In [105]: s.sort_index()
Out[105]:
bar  one   -2.213588
     two    0.206053
baz  one    1.266143
     two    1.063327
foo  one    0.408204
     two    0.299368
qux  one   -0.863838
     two   -0.251905
dtype: float64

In [106]: s.sort_index(level=0)
Out[106]:
bar  one   -2.213588
     two    0.206053
baz  one    1.266143
     two    1.063327
foo  one    0.408204
     two    0.299368
qux  one   -0.863838
     two   -0.251905
dtype: float64

In [107]: s.sort_index(level=1)
Out[107]:
bar  one   -2.213588
baz  one    1.266143
foo  one    0.408204
qux  one   -0.863838
bar  two    0.206053
baz  two    1.063327
foo  two    0.299368
qux  two   -0.251905
dtype: float64
```

You may also pass a level name to `sort_index` if the `MultiIndex` levels are named.

```
In [108]: s.index.set_names(["L1", "L2"], inplace=True)

In [109]: s.sort_index(level="L1")
Out[109]:
L1   L2
bar  one   -2.213588
     two    0.206053
baz  one    1.266143
     two    1.063327
foo  one    0.408204
     two    0.299368
```

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```
qux  one   -0.863838
     two   -0.251905
dtype: float64

In [110]: s.sort_index(level="L2")
Out[110]:
L1   L2
bar  one   -2.213588
baz  one    1.266143
foo  one    0.408204
qux  one   -0.863838
bar  two    0.206053
baz  two    1.063327
foo  two    0.299368
qux  two   -0.251905
dtype: float64
```

On higher dimensional objects, you can sort any of the other axes by level if they have a `MultiIndex`:

```
In [111]: df.T.sort_index(level=1, axis=1)
Out[111]:
        one      zero       one      zero
          x         x         y         y
0  0.600178  2.410179  1.519970  0.132885
1  0.274230  1.450520 -0.493662 -0.023688
```

Indexing will work even if the data are not sorted, but will be rather inefficient (and show a `PerformanceWarning`). It will also return a copy of the data rather than a view:

```
In [112]: dfm = pd.DataFrame(
   .....:     {"jim": [0, 0, 1, 1], "joe": ["x", "x", "z", "y"], "jolie": np.random.
↪rand(4)}
   .....: )
   .....:

In [113]: dfm = dfm.set_index(["jim", "joe"])

In [114]: dfm
Out[114]:
            jolie
jim joe
0   x    0.490671
    x    0.120248
1   z    0.537020
    y    0.110968
```

```
In [4]: dfm.loc[(1, 'z')]
PerformanceWarning: indexing past lexsort depth may impact performance.

Out[4]:
            jolie
jim joe
1   z    0.64094
```

Furthermore, if you try to index something that is not fully lexsorted, this can raise:

```
In [5]: dfm.loc[(0, 'y'):(1, 'z')]
UnsortedIndexError: 'Key length (2) was greater than MultiIndex lexsort depth (1)'
```

The *is_lexsorted()* method on a `MultiIndex` shows if the index is sorted, and the `lexsort_depth` property returns the sort depth:

```
In [115]: dfm.index.is_lexsorted()
Out[115]: False

In [116]: dfm.index.lexsort_depth
Out[116]: 1
```

```
In [117]: dfm = dfm.sort_index()

In [118]: dfm
Out[118]:
             jolie
jim joe
0   x    0.490671
    x    0.120248
1   y    0.110968
    z    0.537020

In [119]: dfm.index.is_lexsorted()
Out[119]: True

In [120]: dfm.index.lexsort_depth
Out[120]: 2
```

And now selection works as expected.

```
In [121]: dfm.loc[(0, "y"):(1, "z")]
Out[121]:
             jolie
jim joe
1   y    0.110968
    z    0.537020
```

2.6.4 Take methods

Similar to NumPy ndarrays, pandas `Index`, `Series`, and `DataFrame` also provides the *take()* method that retrieves elements along a given axis at the given indices. The given indices must be either a list or an ndarray of integer index positions. `take` will also accept negative integers as relative positions to the end of the object.

```
In [122]: index = pd.Index(np.random.randint(0, 1000, 10))

In [123]: index
Out[123]: Int64Index([214, 502, 712, 567, 786, 175, 993, 133, 758, 329], dtype='int64
↪')

In [124]: positions = [0, 9, 3]

In [125]: index[positions]
Out[125]: Int64Index([214, 329, 567], dtype='int64')
```

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```
In [126]: index.take(positions)
Out[126]: Int64Index([214, 329, 567], dtype='int64')

In [127]: ser = pd.Series(np.random.randn(10))

In [128]: ser.iloc[positions]
Out[128]:
0   -0.179666
9    1.824375
3    0.392149
dtype: float64

In [129]: ser.take(positions)
Out[129]:
0   -0.179666
9    1.824375
3    0.392149
dtype: float64
```

For DataFrames, the given indices should be a 1d list or ndarray that specifies row or column positions.

```
In [130]: frm = pd.DataFrame(np.random.randn(5, 3))

In [131]: frm.take([1, 4, 3])
Out[131]:
          0         1         2
1 -1.237881  0.106854 -1.276829
4  0.629675 -1.425966  1.857704
3  0.979542 -1.633678  0.615855

In [132]: frm.take([0, 2], axis=1)
Out[132]:
          0         2
0  0.595974  0.601544
1 -1.237881 -1.276829
2 -0.767101  1.499591
3  0.979542  0.615855
4  0.629675  1.857704
```

It is important to note that the `take` method on pandas objects are not intended to work on boolean indices and may return unexpected results.

```
In [133]: arr = np.random.randn(10)

In [134]: arr.take([False, False, True, True])
Out[134]: array([-1.1935, -1.1935,  0.6775,  0.6775])

In [135]: arr[[0, 1]]
Out[135]: array([-1.1935,  0.6775])

In [136]: ser = pd.Series(np.random.randn(10))

In [137]: ser.take([False, False, True, True])
Out[137]:
0    0.233141
0    0.233141
```

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```
1   -0.223540
1   -0.223540
dtype: float64

In [138]: ser.iloc[[0, 1]]
Out[138]:
0    0.233141
1   -0.223540
dtype: float64
```

Finally, as a small note on performance, because the `take` method handles a narrower range of inputs, it can offer performance that is a good deal faster than fancy indexing.

```
In [139]: arr = np.random.randn(10000, 5)

In [140]: indexer = np.arange(10000)

In [141]: random.shuffle(indexer)

In [142]: %timeit arr[indexer]
   .....: %timeit arr.take(indexer, axis=0)
   .....:
130 us +- 1.11 us per loop (mean +- std. dev. of 7 runs, 10000 loops each)
37.7 us +- 1.06 us per loop (mean +- std. dev. of 7 runs, 10000 loops each)
```

```
In [143]: ser = pd.Series(arr[:, 0])

In [144]: %timeit ser.iloc[indexer]
   .....: %timeit ser.take(indexer)
   .....:
69.6 us +- 364 ns per loop (mean +- std. dev. of 7 runs, 10000 loops each)
61.8 us +- 728 ns per loop (mean +- std. dev. of 7 runs, 10000 loops each)
```

2.6.5 Index types

We have discussed `MultiIndex` in the previous sections pretty extensively. Documentation about `DatetimeIndex` and `PeriodIndex` are shown *here*, and documentation about `TimedeltaIndex` is found *here*.

In the following sub-sections we will highlight some other index types.

CategoricalIndex

`CategoricalIndex` is a type of index that is useful for supporting indexing with duplicates. This is a container around a *`Categorical`* and allows efficient indexing and storage of an index with a large number of duplicated elements.

```
In [145]: from pandas.api.types import CategoricalDtype

In [146]: df = pd.DataFrame({"A": np.arange(6), "B": list("aabbca")})

In [147]: df["B"] = df["B"].astype(CategoricalDtype(list("cab")))
```

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```
In [148]: df
Out[148]:
   A  B
0  0  a
1  1  a
2  2  b
3  3  b
4  4  c
5  5  a

In [149]: df.dtypes
Out[149]:
A       int64
B    category
dtype: object

In [150]: df["B"].cat.categories
Out[150]: Index(['c', 'a', 'b'], dtype='object')
```

Setting the index will create a `CategoricalIndex`.

```
In [151]: df2 = df.set_index("B")

In [152]: df2.index
Out[152]: CategoricalIndex(['a', 'a', 'b', 'b', 'c', 'a'], categories=['c', 'a', 'b'],
↪ ordered=False, name='B', dtype='category')
```

Indexing with `__getitem__/.iloc/.loc` works similarly to an `Index` with duplicates. The indexers **must** be in the category or the operation will raise a `KeyError`.

```
In [153]: df2.loc["a"]
Out[153]:
   A
B
a  0
a  1
a  5
```

The `CategoricalIndex` is **preserved** after indexing:

```
In [154]: df2.loc["a"].index
Out[154]: CategoricalIndex(['a', 'a', 'a'], categories=['c', 'a', 'b'], ordered=False,
↪ name='B', dtype='category')
```

Sorting the index will sort by the order of the categories (recall that we created the index with `CategoricalDtype(list('cab'))`, so the sorted order is `cab`).

```
In [155]: df2.sort_index()
Out[155]:
   A
B
c  4
a  0
a  1
a  5
b  2
b  3
```

Groupby operations on the index will preserve the index nature as well.

```
In [156]: df2.groupby(level=0).sum()
Out[156]:
   A
B
c  4
a  6
b  5

In [157]: df2.groupby(level=0).sum().index
Out[157]: CategoricalIndex(['c', 'a', 'b'], categories=['c', 'a', 'b'], ordered=False,
↪ name='B', dtype='category')
```

Reindexing operations will return a resulting index based on the type of the passed indexer. Passing a list will return a plain-old `Index`; indexing with a `Categorical` will return a `CategoricalIndex`, indexed according to the categories of the **passed** `Categorical` dtype. This allows one to arbitrarily index these even with values **not** in the categories, similarly to how you can reindex **any** pandas index.

```
In [158]: df3 = pd.DataFrame(
   .....:     {"A": np.arange(3), "B": pd.Series(list("abc")).astype("category")}
   .....: )
   .....:

In [159]: df3 = df3.set_index("B")

In [160]: df3
Out[160]:
   A
B
a  0
b  1
c  2
```

```
In [161]: df3.reindex(["a", "e"])
Out[161]:
     A
B
a  0.0
e  NaN

In [162]: df3.reindex(["a", "e"]).index
Out[162]: Index(['a', 'e'], dtype='object', name='B')

In [163]: df3.reindex(pd.Categorical(["a", "e"], categories=list("abe")))
Out[163]:
     A
B
a  0.0
e  NaN

In [164]: df3.reindex(pd.Categorical(["a", "e"], categories=list("abe"))).index
Out[164]: CategoricalIndex(['a', 'e'], categories=['a', 'b', 'e'], ordered=False,␣
↪name='B', dtype='category')
```

Warning: Reshaping and Comparison operations on a `CategoricalIndex` must have the same categories or a `TypeError` will be raised.

```
In [165]: df4 = pd.DataFrame({"A": np.arange(2), "B": list("ba")})

In [166]: df4["B"] = df4["B"].astype(CategoricalDtype(list("ab")))

In [167]: df4 = df4.set_index("B")

In [168]: df4.index
Out[168]: CategoricalIndex(['b', 'a'], categories=['a', 'b'], ordered=False, name='B
↪', dtype='category')

In [169]: df5 = pd.DataFrame({"A": np.arange(2), "B": list("bc")})

In [170]: df5["B"] = df5["B"].astype(CategoricalDtype(list("bc")))

In [171]: df5 = df5.set_index("B")

In [172]: df5.index
Out[172]: CategoricalIndex(['b', 'c'], categories=['b', 'c'], ordered=False, name='B
↪', dtype='category')
```

```
In [1]: pd.concat([df4, df5])
TypeError: categories must match existing categories when appending
```

Int64Index and RangeIndex

Int64Index is a fundamental basic index in pandas. This is an immutable array implementing an ordered, sliceable set.

RangeIndex is a sub-class of `Int64Index` that provides the default index for all `NDFrame` objects. `RangeIndex` is an optimized version of `Int64Index` that can represent a monotonic ordered set. These are analogous to Python range types.

Float64Index

By default a *Float64Index* will be automatically created when passing floating, or mixed-integer-floating values in index creation. This enables a pure label-based slicing paradigm that makes `[],ix,loc` for scalar indexing and slicing work exactly the same.

```
In [173]: indexf = pd.Index([1.5, 2, 3, 4.5, 5])

In [174]: indexf
Out[174]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')

In [175]: sf = pd.Series(range(5), index=indexf)

In [176]: sf
Out[176]:
1.5    0
2.0    1
3.0    2
4.5    3
```

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```
5.0    4
dtype: int64
```

Scalar selection for `[],.loc` will always be label based. An integer will match an equal float index (e.g. `3` is equivalent to `3.0`).

```
In [177]: sf[3]
Out[177]: 2

In [178]: sf[3.0]
Out[178]: 2

In [179]: sf.loc[3]
Out[179]: 2

In [180]: sf.loc[3.0]
Out[180]: 2
```

The only positional indexing is via `iloc`.

```
In [181]: sf.iloc[3]
Out[181]: 3
```

A scalar index that is not found will raise a `KeyError`. Slicing is primarily on the values of the index when using `[],ix,loc`, and **always** positional when using `iloc`. The exception is when the slice is boolean, in which case it will always be positional.

```
In [182]: sf[2:4]
Out[182]:
2.0    1
3.0    2
dtype: int64

In [183]: sf.loc[2:4]
Out[183]:
2.0    1
3.0    2
dtype: int64

In [184]: sf.iloc[2:4]
Out[184]:
3.0    2
4.5    3
dtype: int64
```

In float indexes, slicing using floats is allowed.

```
In [185]: sf[2.1:4.6]
Out[185]:
3.0    2
4.5    3
dtype: int64

In [186]: sf.loc[2.1:4.6]
Out[186]:
3.0    2
```

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```
4.5    3
dtype: int64
```

In non-float indexes, slicing using floats will raise a `TypeError`.

```
In [1]: pd.Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type (Int64Index)

In [1]: pd.Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type␣
↪(Int64Index)
```

Here is a typical use-case for using this type of indexing. Imagine that you have a somewhat irregular timedelta-like indexing scheme, but the data is recorded as floats. This could, for example, be millisecond offsets.

```
In [187]: dfir = pd.concat(
   .....:     [
   .....:         pd.DataFrame(
   .....:             np.random.randn(5, 2), index=np.arange(5) * 250.0, columns=list(
↪"AB")
   .....:         ),
   .....:         pd.DataFrame(
   .....:             np.random.randn(6, 2),
   .....:             index=np.arange(4, 10) * 250.1,
   .....:             columns=list("AB"),
   .....:         ),
   .....:     ]
   .....: )
   .....:

In [188]: dfir
Out[188]:
                A         B
0.0     -0.435772 -1.188928
250.0   -0.808286 -0.284634
500.0   -1.815703  1.347213
750.0   -0.243487  0.514704
1000.0   1.162969 -0.287725
1000.4  -0.179734  0.993962
1250.5  -0.212673  0.909872
1500.6  -0.733333 -0.349893
1750.7   0.456434 -0.306735
2000.8   0.553396  0.166221
2250.9  -0.101684 -0.734907
```

Selection operations then will always work on a value basis, for all selection operators.

```
In [189]: dfir[0:1000.4]
Out[189]:
                A         B
0.0     -0.435772 -1.188928
250.0   -0.808286 -0.284634
500.0   -1.815703  1.347213
750.0   -0.243487  0.514704
1000.0   1.162969 -0.287725
1000.4  -0.179734  0.993962
```

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```
In [190]: dfir.loc[0:1001, "A"]
Out[190]:
0.0      -0.435772
250.0    -0.808286
500.0    -1.815703
750.0    -0.243487
1000.0    1.162969
1000.4   -0.179734
Name: A, dtype: float64

In [191]: dfir.loc[1000.4]
Out[191]:
A   -0.179734
B    0.993962
Name: 1000.4, dtype: float64
```

You could retrieve the first 1 second (1000 ms) of data as such:

```
In [192]: dfir[0:1000]
Out[192]:
                A         B
0.0    -0.435772 -1.188928
250.0  -0.808286 -0.284634
500.0  -1.815703  1.347213
750.0  -0.243487  0.514704
1000.0  1.162969 -0.287725
```

If you need integer based selection, you should use `iloc`:

```
In [193]: dfir.iloc[0:5]
Out[193]:
                A         B
0.0    -0.435772 -1.188928
250.0  -0.808286 -0.284634
500.0  -1.815703  1.347213
750.0  -0.243487  0.514704
1000.0  1.162969 -0.287725
```

IntervalIndex

IntervalIndex together with its own dtype, `IntervalDtype` as well as the *Interval* scalar type, allow first-class support in pandas for interval notation.

The `IntervalIndex` allows some unique indexing and is also used as a return type for the categories in *cut()* and *qcut()*.

Indexing with an `IntervalIndex`

An `IntervalIndex` can be used in `Series` and in `DataFrame` as the index.

```
In [194]: df = pd.DataFrame(
   .....:     {"A": [1, 2, 3, 4]}, index=pd.IntervalIndex.from_breaks([0, 1, 2, 3, 4])
   .....: )
   .....:

In [195]: df
Out[195]:
         A
(0, 1]   1
(1, 2]   2
(2, 3]   3
(3, 4]   4
```

Label based indexing via `.loc` along the edges of an interval works as you would expect, selecting that particular interval.

```
In [196]: df.loc[2]
Out[196]:
A    2
Name: (1, 2], dtype: int64

In [197]: df.loc[[2, 3]]
Out[197]:
         A
(1, 2]   2
(2, 3]   3
```

If you select a label *contained* within an interval, this will also select the interval.

```
In [198]: df.loc[2.5]
Out[198]:
A    3
Name: (2, 3], dtype: int64

In [199]: df.loc[[2.5, 3.5]]
Out[199]:
         A
(2, 3]   3
(3, 4]   4
```

Selecting using an `Interval` will only return exact matches (starting from pandas 0.25.0).

```
In [200]: df.loc[pd.Interval(1, 2)]
Out[200]:
A    2
Name: (1, 2], dtype: int64
```

Trying to select an `Interval` that is not exactly contained in the `IntervalIndex` will raise a `KeyError`.

```
In [7]: df.loc[pd.Interval(0.5, 2.5)]
---------------------------------------------------------------------------
KeyError: Interval(0.5, 2.5, closed='right')
```

Selecting all `Intervals` that overlap a given `Interval` can be performed using the *`overlaps()`* method to create a boolean indexer.

```
In [201]: idxr = df.index.overlaps(pd.Interval(0.5, 2.5))

In [202]: idxr
Out[202]: array([ True,  True,  True, False])

In [203]: df[idxr]
Out[203]:
        A
(0, 1]  1
(1, 2]  2
(2, 3]  3
```

Binning data with `cut` and `qcut`

`cut()` and *`qcut()`* both return a `Categorical` object, and the bins they create are stored as an `IntervalIndex` in its `.categories` attribute.

```
In [204]: c = pd.cut(range(4), bins=2)

In [205]: c
Out[205]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3.0], (1.5, 3.0]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]

In [206]: c.categories
Out[206]:
IntervalIndex([(-0.003, 1.5], (1.5, 3.0]],
              closed='right',
              dtype='interval[float64]')
```

`cut()` also accepts an `IntervalIndex` for its `bins` argument, which enables a useful pandas idiom. First, We call *`cut()`* with some data and `bins` set to a fixed number, to generate the bins. Then, we pass the values of `.categories` as the `bins` argument in subsequent calls to *`cut()`*, supplying new data which will be binned into the same bins.

```
In [207]: pd.cut([0, 3, 5, 1], bins=c.categories)
Out[207]:
[(-0.003, 1.5], (1.5, 3.0], NaN, (-0.003, 1.5]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]
```

Any value which falls outside all bins will be assigned a `NaN` value.

Generating ranges of intervals

If we need intervals on a regular frequency, we can use the *interval_range()* function to create an IntervalIndex using various combinations of start, end, and periods. The default frequency for interval_range is a 1 for numeric intervals, and calendar day for datetime-like intervals:

```
In [208]: pd.interval_range(start=0, end=5)
Out[208]:
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]],
              closed='right',
              dtype='interval[int64]')

In [209]: pd.interval_range(start=pd.Timestamp("2017-01-01"), periods=4)
Out[209]:
IntervalIndex([(2017-01-01, 2017-01-02], (2017-01-02, 2017-01-03], (2017-01-03, 2017-
↪01-04], (2017-01-04, 2017-01-05]],
              closed='right',
              dtype='interval[datetime64[ns]]')

In [210]: pd.interval_range(end=pd.Timedelta("3 days"), periods=3)
Out[210]:
IntervalIndex([(0 days 00:00:00, 1 days 00:00:00], (1 days 00:00:00, 2 days 00:00:00],
↪ (2 days 00:00:00, 3 days 00:00:00]],
              closed='right',
              dtype='interval[timedelta64[ns]]')
```

The freq parameter can used to specify non-default frequencies, and can utilize a variety of *frequency aliases* with datetime-like intervals:

```
In [211]: pd.interval_range(start=0, periods=5, freq=1.5)
Out[211]:
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0], (6.0, 7.5]],
              closed='right',
              dtype='interval[float64]')

In [212]: pd.interval_range(start=pd.Timestamp("2017-01-01"), periods=4, freq="W")
Out[212]:
IntervalIndex([(2017-01-01, 2017-01-08], (2017-01-08, 2017-01-15], (2017-01-15, 2017-
↪01-22], (2017-01-22, 2017-01-29]],
              closed='right',
              dtype='interval[datetime64[ns]]')

In [213]: pd.interval_range(start=pd.Timedelta("0 days"), periods=3, freq="9H")
Out[213]:
IntervalIndex([(0 days 00:00:00, 0 days 09:00:00], (0 days 09:00:00, 0 days 18:00:00],
↪ (0 days 18:00:00, 1 days 03:00:00]],
              closed='right',
              dtype='interval[timedelta64[ns]]')
```

Additionally, the closed parameter can be used to specify which side(s) the intervals are closed on. Intervals are closed on the right side by default.

```
In [214]: pd.interval_range(start=0, end=4, closed="both")
Out[214]:
IntervalIndex([[0, 1], [1, 2], [2, 3], [3, 4]],
              closed='both',
              dtype='interval[int64]')
```

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```
In [215]: pd.interval_range(start=0, end=4, closed="neither")
Out[215]:
IntervalIndex([(0, 1), (1, 2), (2, 3), (3, 4)],
              closed='neither',
              dtype='interval[int64]')
```

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced intervals from `start` to `end` inclusively, with `periods` number of elements in the resulting `IntervalIndex`:

```
In [216]: pd.interval_range(start=0, end=6, periods=4)
Out[216]:
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]],
              closed='right',
              dtype='interval[float64]')

In [217]: pd.interval_range(pd.Timestamp("2018-01-01"), pd.Timestamp("2018-02-28"),␣
↪periods=3)
Out[217]:
IntervalIndex([(2018-01-01, 2018-01-20 08:00:00], (2018-01-20 08:00:00, 2018-02-08 16:
↪00:00], (2018-02-08 16:00:00, 2018-02-28]],
              closed='right',
              dtype='interval[datetime64[ns]]')
```

2.6.6 Miscellaneous indexing FAQ

Integer indexing

Label-based indexing with integer axis labels is a thorny topic. It has been discussed heavily on mailing lists and among various members of the scientific Python community. In pandas, our general viewpoint is that labels matter more than integer locations. Therefore, with an integer axis index *only* label-based indexing is possible with the standard tools like `.loc`. The following code will generate exceptions:

```
In [218]: s = pd.Series(range(5))

In [219]: s[-1]
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
/pandas/pandas/core/indexes/range.py in get_loc(self, key, method, tolerance)
    350                 try:
--> 351                     return self._range.index(new_key)
    352                 except ValueError as err:

ValueError: -1 is not in range

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
<ipython-input-219-76c3dce40054> in <module>
----> 1 s[-1]

/pandas/pandas/core/series.py in __getitem__(self, key)
    849
    850         elif key_is_scalar:
```

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```
--> 851             return self._get_value(key)
    852
    853         if is_hashable(key):

/pandas/pandas/core/series.py in _get_value(self, label, takeable)
    957
    958         # Similar to Index.get_value, but we do not fall back to positional
--> 959         loc = self.index.get_loc(label)
    960         return self.index._get_values_for_loc(self, loc, label)
    961

/pandas/pandas/core/indexes/range.py in get_loc(self, key, method, tolerance)
    351                     return self._range.index(new_key)
    352                 except ValueError as err:
--> 353                     raise KeyError(key) from err
    354             raise KeyError(key)
    355         return super().get_loc(key, method=method, tolerance=tolerance)

KeyError: -1

In [220]: df = pd.DataFrame(np.random.randn(5, 4))

In [221]: df
Out[221]:
          0         1         2         3
0 -0.130121 -0.476046  0.759104  0.213379
1 -0.082641  0.448008  0.656420 -1.051443
2  0.594956 -0.151360 -0.069303  1.221431
3 -0.182832  0.791235  0.042745  2.069775
4  1.446552  0.019814 -1.389212 -0.702312

In [222]: df.loc[-2:]
Out[222]:
          0         1         2         3
0 -0.130121 -0.476046  0.759104  0.213379
1 -0.082641  0.448008  0.656420 -1.051443
2  0.594956 -0.151360 -0.069303  1.221431
3 -0.182832  0.791235  0.042745  2.069775
4  1.446552  0.019814 -1.389212 -0.702312
```

This deliberate decision was made to prevent ambiguities and subtle bugs (many users reported finding bugs when the API change was made to stop "falling back" on position-based indexing).

Non-monotonic indexes require exact matches

If the index of a `Series` or `DataFrame` is monotonically increasing or decreasing, then the bounds of a label-based slice can be outside the range of the index, much like slice indexing a normal Python `list`. Monotonicity of an index can be tested with the *`is_monotonic_increasing()`* and *`is_monotonic_decreasing()`* attributes.

```
In [223]: df = pd.DataFrame(index=[2, 3, 3, 4, 5], columns=["data"],␣
↪data=list(range(5)))

In [224]: df.index.is_monotonic_increasing
Out[224]: True
```

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```
# no rows 0 or 1, but still returns rows 2, 3 (both of them), and 4:
In [225]: df.loc[0:4, :]
Out[225]:
   data
2     0
3     1
3     2
4     3

# slice is are outside the index, so empty DataFrame is returned
In [226]: df.loc[13:15, :]
Out[226]:
Empty DataFrame
Columns: [data]
Index: []
```

On the other hand, if the index is not monotonic, then both slice bounds must be *unique* members of the index.

```
In [227]: df = pd.DataFrame(index=[2, 3, 1, 4, 3, 5], columns=["data"],␣
↪data=list(range(6)))

In [228]: df.index.is_monotonic_increasing
Out[228]: False

# OK because 2 and 4 are in the index
In [229]: df.loc[2:4, :]
Out[229]:
   data
2     0
3     1
1     2
4     3
```

```
# 0 is not in the index
In [9]: df.loc[0:4, :]
KeyError: 0

# 3 is not a unique label
In [11]: df.loc[2:3, :]
KeyError: 'Cannot get right slice bound for non-unique label: 3'
```

`Index.is_monotonic_increasing` and `Index.is_monotonic_decreasing` only check that an index is weakly monotonic. To check for strict monotonicity, you can combine one of those with the *`is_unique()`* attribute.

```
In [230]: weakly_monotonic = pd.Index(["a", "b", "c", "c"])

In [231]: weakly_monotonic
Out[231]: Index(['a', 'b', 'c', 'c'], dtype='object')

In [232]: weakly_monotonic.is_monotonic_increasing
Out[232]: True

In [233]: weakly_monotonic.is_monotonic_increasing & weakly_monotonic.is_unique
Out[233]: False
```

Endpoints are inclusive

Compared with standard Python sequence slicing in which the slice endpoint is not inclusive, label-based slicing in pandas **is inclusive**. The primary reason for this is that it is often not possible to easily determine the "successor" or next element after a particular label in an index. For example, consider the following `Series`:

```
In [234]: s = pd.Series(np.random.randn(6), index=list("abcdef"))

In [235]: s
Out[235]:
a    0.301379
b    1.240445
c   -0.846068
d   -0.043312
e   -1.658747
f   -0.819549
dtype: float64
```

Suppose we wished to slice from `c` to `e`, using integers this would be accomplished as such:

```
In [236]: s[2:5]
Out[236]:
c   -0.846068
d   -0.043312
e   -1.658747
dtype: float64
```

However, if you only had `c` and `e`, determining the next element in the index can be somewhat complicated. For example, the following does not work:

```
s.loc['c':'e' + 1]
```

A very common use case is to limit a time series to start and end at two specific dates. To enable this, we made the design choice to make label-based slicing include both endpoints:

```
In [237]: s.loc["c":"e"]
Out[237]:
c   -0.846068
d   -0.043312
e   -1.658747
dtype: float64
```

This is most definitely a "practicality beats purity" sort of thing, but it is something to watch out for if you expect label-based slicing to behave exactly in the way that standard Python integer slicing works.

Indexing potentially changes underlying Series dtype

The different indexing operation can potentially change the dtype of a `Series`.

```
In [238]: series1 = pd.Series([1, 2, 3])

In [239]: series1.dtype
Out[239]: dtype('int64')

In [240]: res = series1.reindex([0, 4])
```

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```
In [241]: res.dtype
Out[241]: dtype('float64')

In [242]: res
Out[242]:
0    1.0
4    NaN
dtype: float64
```

```
In [243]: series2 = pd.Series([True])

In [244]: series2.dtype
Out[244]: dtype('bool')

In [245]: res = series2.reindex_like(series1)

In [246]: res.dtype
Out[246]: dtype('O')

In [247]: res
Out[247]:
0    True
1     NaN
2     NaN
dtype: object
```

This is because the (re)indexing operations above silently inserts `NaNs` and the `dtype` changes accordingly. This can cause some issues when using `numpy ufuncs` such as `numpy.logical_and`.

See the this old issue for a more detailed discussion.

2.7 Merge, join, concatenate and compare

pandas provides various facilities for easily combining together Series or DataFrame with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

In addition, pandas also provides utilities to compare two Series or DataFrame and summarize their differences.

2.7.1 Concatenating objects

The *concat()* function (in the main pandas namespace) does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes. Note that I say "if any" because there is only a single possible axis of concatenation for Series.

Before diving into all of the details of `concat` and what it can do, here is a simple example:

```
In [1]: df1 = pd.DataFrame(
   ...:     {
   ...:         "A": ["A0", "A1", "A2", "A3"],
   ...:         "B": ["B0", "B1", "B2", "B3"],
   ...:         "C": ["C0", "C1", "C2", "C3"],
   ...:         "D": ["D0", "D1", "D2", "D3"],
   ...:     },
```

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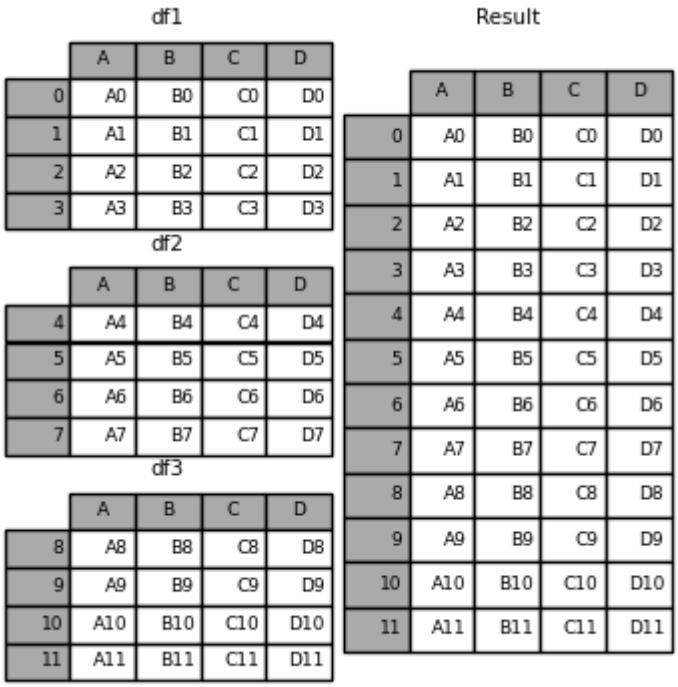
```
   ...:     index=[0, 1, 2, 3],
   ...: )
   ...:

In [2]: df2 = pd.DataFrame(
   ...:     {
   ...:         "A": ["A4", "A5", "A6", "A7"],
   ...:         "B": ["B4", "B5", "B6", "B7"],
   ...:         "C": ["C4", "C5", "C6", "C7"],
   ...:         "D": ["D4", "D5", "D6", "D7"],
   ...:     },
   ...:     index=[4, 5, 6, 7],
   ...: )
   ...:

In [3]: df3 = pd.DataFrame(
   ...:     {
   ...:         "A": ["A8", "A9", "A10", "A11"],
   ...:         "B": ["B8", "B9", "B10", "B11"],
   ...:         "C": ["C8", "C9", "C10", "C11"],
   ...:         "D": ["D8", "D9", "D10", "D11"],
   ...:     },
   ...:     index=[8, 9, 10, 11],
   ...: )
   ...:

In [4]: frames = [df1, df2, df3]

In [5]: result = pd.concat(frames)
```



Like its sibling function on ndarrays, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of "what to do with the other axes":

```
pd.concat(
    objs,
    axis=0,
    join="outer",
    ignore_index=False,
    keys=None,
    levels=None,
    names=None,
    verify_integrity=False,
    copy=True,
)
```

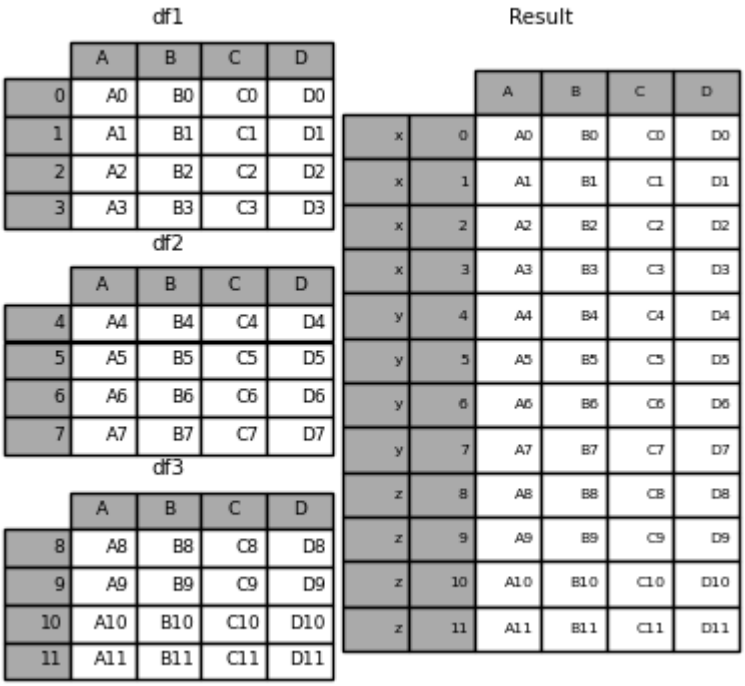
- `objs` : a sequence or mapping of Series or DataFrame objects. If a dict is passed, the sorted keys will be used as the `keys` argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a ValueError will be raised.
- `axis` : {0, 1, ...}, default 0. The axis to concatenate along.
- `join` : {'inner', 'outer'}, default 'outer'. How to handle indexes on other axis(es). Outer for union and inner for intersection.
- `ignore_index` : boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.
- `keys` : sequence, default None. Construct hierarchical index using the passed keys as the outermost level. If multiple levels passed, should contain tuples.

- `levels` : list of sequences, default None. Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.
- `names` : list, default None. Names for the levels in the resulting hierarchical index.
- `verify_integrity` : boolean, default False. Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.
- `copy` : boolean, default True. If False, do not copy data unnecessarily.

Without a little bit of context many of these arguments don't make much sense. Let's revisit the above example. Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this using the `keys` argument:

```
In [6]: result = pd.concat(frames, keys=["x", "y", "z"])
```

```
```



As you can see (if you've read the rest of the documentation), the resulting object's index has a *hierarchical index*. This means that we can now select out each chunk by key:

```
In [7]: result.loc["y"]
Out[7]:
    A   B   C   D
4  A4  B4  C4  D4
5  A5  B5  C5  D5
6  A6  B6  C6  D6
7  A7  B7  C7  D7
```

It's not a stretch to see how this can be very useful. More detail on this functionality below.

Note: It is worth noting that *`concat()`* (and therefore `append()`) makes a full copy of the data, and that constantly

reusing this function can create a significant performance hit. If you need to use the operation over several datasets, use a list comprehension.

```
frames = [ process_your_file(f) for f in files ]
result = pd.concat(frames)
```

Note: When concatenating DataFrames with named axes, pandas will attempt to preserve these index/column names whenever possible. In the case where all inputs share a common name, this name will be assigned to the result. When the input names do not all agree, the result will be unnamed. The same is true for *MultiIndex*, but the logic is applied separately on a level-by-level basis.

Set logic on the other axes

When gluing together multiple DataFrames, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in the following two ways:

- Take the union of them all, `join='outer'`. This is the default option as it results in zero information loss.
- Take the intersection, `join='inner'`.

Here is an example of each of these methods. First, the default `join='outer'` behavior:

```
In [8]: df4 = pd.DataFrame(
   ...:     {
   ...:         "B": ["B2", "B3", "B6", "B7"],
   ...:         "D": ["D2", "D3", "D6", "D7"],
   ...:         "F": ["F2", "F3", "F6", "F7"],
   ...:     },
   ...:     index=[2, 3, 6, 7],
   ...: )
   ...:

In [9]: result = pd.concat([df1, df4], axis=1)
```

```

```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3
6	NaN	NaN	NaN	NaN	B6	D6	F6
7	NaN	NaN	NaN	NaN	B7	D7	F7

Here is the same thing with `join='inner'`:

```
In [10]: result = pd.concat([df1, df4], axis=1, join="inner")
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

Lastly, suppose we just wanted to reuse the *exact index* from the original DataFrame:

```
In [11]: result = pd.concat([df1, df4], axis=1).reindex(df1.index)
```

Similarly, we could index before the concatenation:

```
In [12]: pd.concat([df1, df4.reindex(df1.index)], axis=1)
Out[12]:
    A   B   C   D    B    D    F
0  A0  B0  C0  D0  NaN  NaN  NaN
1  A1  B1  C1  D1  NaN  NaN  NaN
2  A2  B2  C2  D2   B2   D2   F2
3  A3  B3  C3  D3   B3   D3   F3
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

Concatenating using `append`

A useful shortcut to *`concat()`* are the *`append()`* instance methods on `Series` and `DataFrame`. These methods actually predated `concat`. They concatenate along `axis=0`, namely the index:

```
In [13]: result = df1.append(df2)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df2

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

Result

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

In the case of `DataFrame`, the indexes must be disjoint but the columns do not need to be:

```
In [14]: result = df1.append(df4, sort=False)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

df4

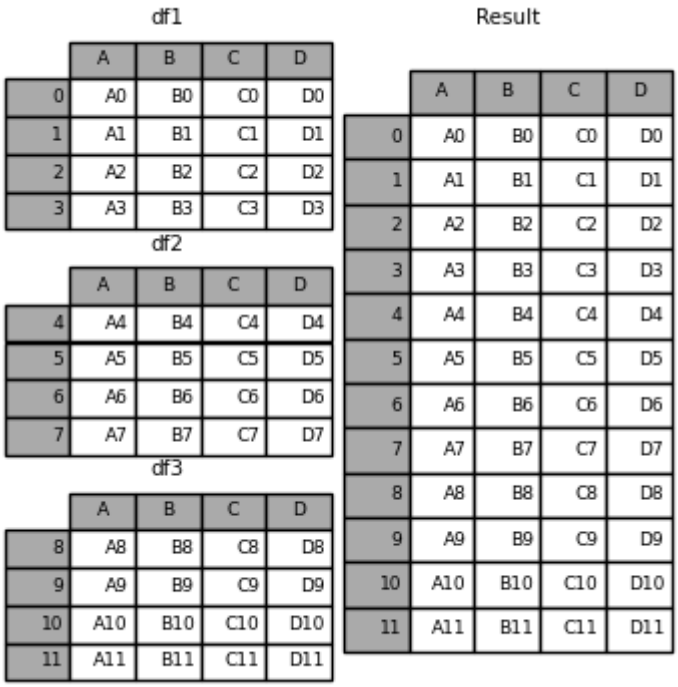
	B	D	F
2	B2	D2	F2
3	B3	D3	F3
6	B6	D6	F6
7	B7	D7	F7

Result

	A	B	C	D	F
0	A0	B0	C0	D0	NaN
1	A1	B1	C1	D1	NaN
2	A2	B2	C2	D2	NaN
3	A3	B3	C3	D3	NaN
2	NaN	B2	NaN	D2	F2
3	NaN	B3	NaN	D3	F3
6	NaN	B6	NaN	D6	F6
7	NaN	B7	NaN	D7	F7

`append` may take multiple objects to concatenate:

```
In [15]: result = df1.append([df2, df3])
```



	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

	A	B	C	D
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

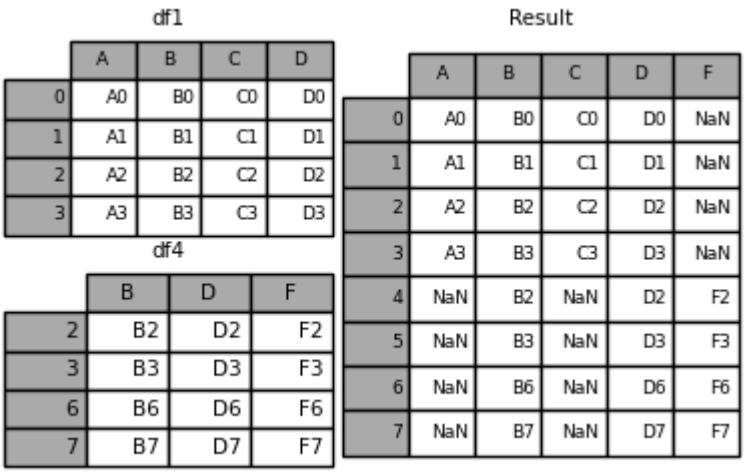
	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7
8	A8	B8	C8	D8
9	A9	B9	C9	D9
10	A10	B10	C10	D10
11	A11	B11	C11	D11

Note: Unlike the `append()` method, which appends to the original list and returns `None`, *`append()`* here **does not** modify `df1` and returns its copy with `df2` appended.

Ignoring indexes on the concatenation axis

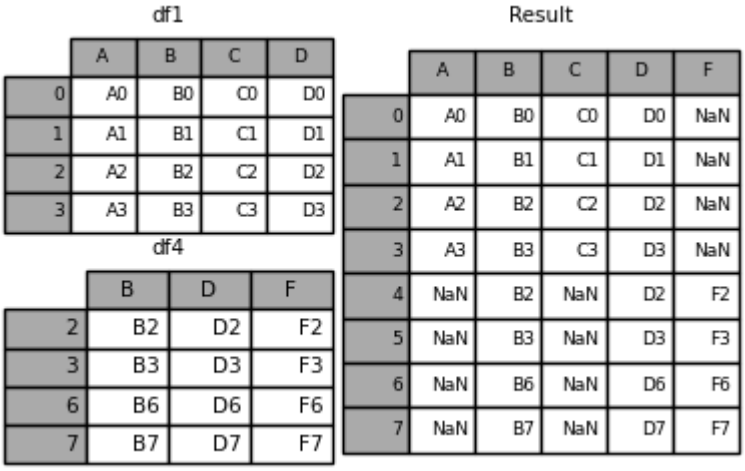
For `DataFrame` objects which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes. To do this, use the `ignore_index` argument:

```
In [16]: result = pd.concat([df1, df4], ignore_index=True, sort=False)
```



This is also a valid argument to *DataFrame.append()*:

```
In [17]: result = df1.append(df4, ignore_index=True, sort=False)
```



Concatenating with mixed ndims

You can concatenate a mix of `Series` and `DataFrame` objects. The `Series` will be transformed to `DataFrame` with the column name as the name of the `Series`.

```
In [18]: s1 = pd.Series(["X0", "X1", "X2", "X3"], name="X")

In [19]: result = pd.concat([df1, s1], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s1

	X
0	X0
1	X1
2	X2
3	X3

Result

	A	B	C	D	X
0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3

Note: Since we're concatenating a `Series` to a `DataFrame`, we could have achieved the same result with *`DataFrame.assign()`*. To concatenate an arbitrary number of pandas objects (`DataFrame` or `Series`), use `concat`.

If unnamed `Series` are passed they will be numbered consecutively.

```
In [20]: s2 = pd.Series(["_0", "_1", "_2", "_3"])

In [21]: result = pd.concat([df1, s2, s2, s2], axis=1)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s2

0	_0
1	_1
2	_2
3	_3

Result

	A	B	C	D	0	1	2
0	A0	B0	C0	D0	_0	_0	_0
1	A1	B1	C1	D1	_1	_1	_1
2	A2	B2	C2	D2	_2	_2	_2
3	A3	B3	C3	D3	_3	_3	_3

Passing `ignore_index=True` will drop all name references.

```
In [22]: result = pd.concat([df1, s1], axis=1, ignore_index=True)
```

df1

	A	B	C	D
0	A0	B0	C0	D0
1	A1	B1	C1	D1
2	A2	B2	C2	D2
3	A3	B3	C3	D3

s1

	X
0	X0
1	X1
2	X2
3	X3

Result

	0	1	2	3	4
0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3

More concatenating with group keys

A fairly common use of the `keys` argument is to override the column names when creating a new `DataFrame` based on existing `Series`. Notice how the default behaviour consists on letting the resulting `DataFrame` inherit the parent `Series`' name, when these existed.

```
In [23]: s3 = pd.Series([0, 1, 2, 3], name="foo")

In [24]: s4 = pd.Series([0, 1, 2, 3])

In [25]: s5 = pd.Series([0, 1, 4, 5])

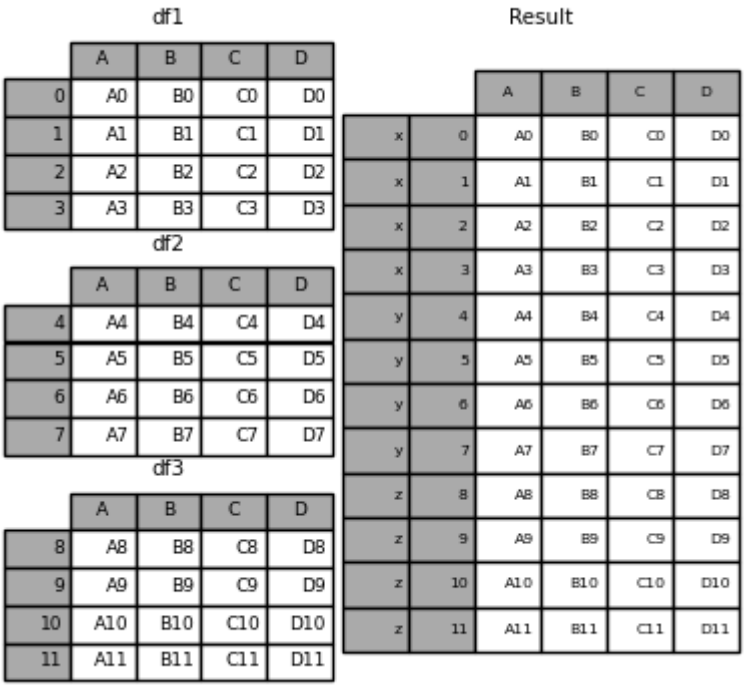
In [26]: pd.concat([s3, s4, s5], axis=1)
Out[26]:
   foo  0  1
0    0  0  0
1    1  1  1
2    2  2  4
3    3  3  5
```

Through the `keys` argument we can override the existing column names.

```
In [27]: pd.concat([s3, s4, s5], axis=1, keys=["red", "blue", "yellow"])
Out[27]:
   red  blue  yellow
0    0     0       0
1    1     1       1
2    2     2       4
3    3     3       5
```

Let's consider a variation of the very first example presented:

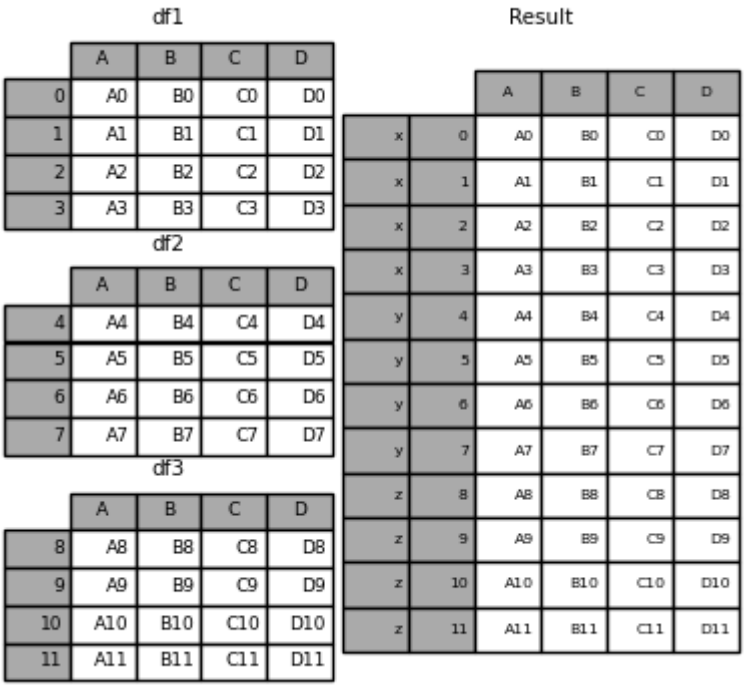
```
In [28]: result = pd.concat(frames, keys=["x", "y", "z"])
```



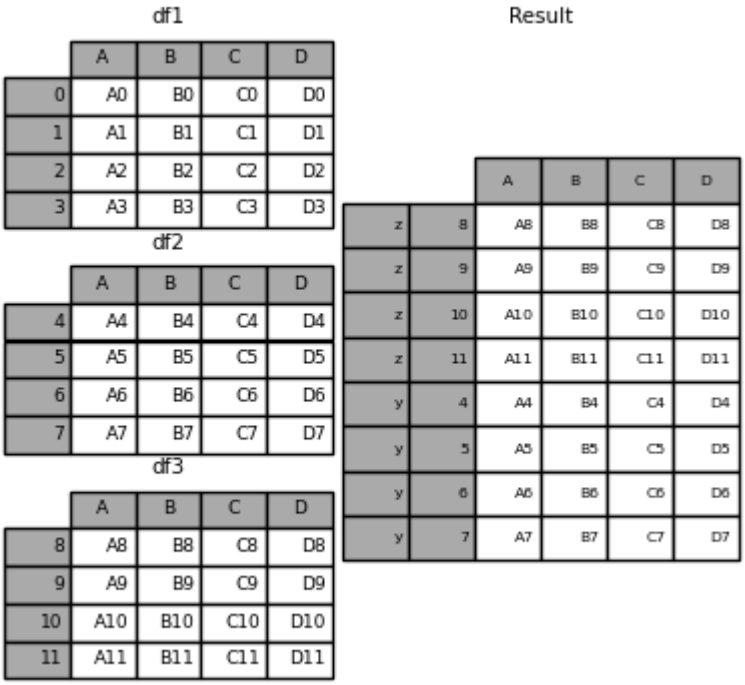
You can also pass a dict to `concat` in which case the dict keys will be used for the `keys` argument (unless other keys are specified):

```
In [29]: pieces = {"x": df1, "y": df2, "z": df3}

In [30]: result = pd.concat(pieces)
```




```
In [31]: result = pd.concat(pieces, keys=["z", "y"])
```

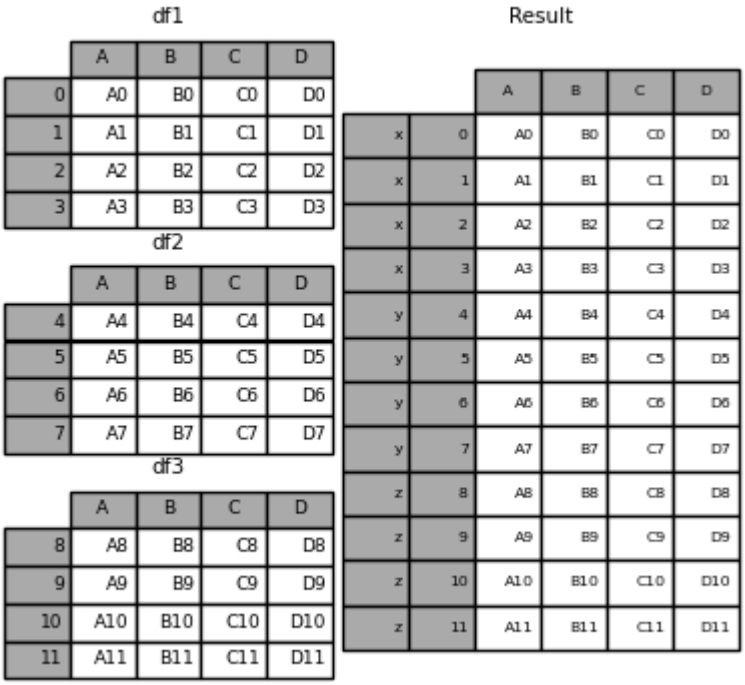


The MultiIndex created has levels that are constructed from the passed keys and the index of the `DataFrame` pieces:

```
In [32]: result.index.levels
Out[32]: FrozenList([['z', 'y'], [4, 5, 6, 7, 8, 9, 10, 11]])
```

If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```
In [33]: result = pd.concat(
   ....:     pieces, keys=["x", "y", "z"], levels=[["z", "y", "x", "w"]], names=[
↪"group_key"]
   ....: )
   ....:
```




```
In [34]: result.index.levels
Out[34]: FrozenList([['z', 'y', 'x', 'w'], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]])
```

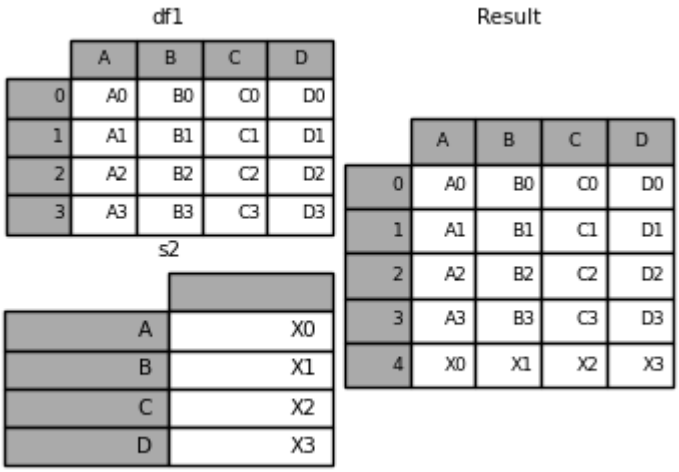
This is fairly esoteric, but it is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

Appending rows to a DataFrame

While not especially efficient (since a new object must be created), you can append a single row to a `DataFrame` by passing a `Series` or dict to `append`, which returns a new `DataFrame` as above.

```
In [35]: s2 = pd.Series(["X0", "X1", "X2", "X3"], index=["A", "B", "C", "D"])

In [36]: result = df1.append(s2, ignore_index=True)
```

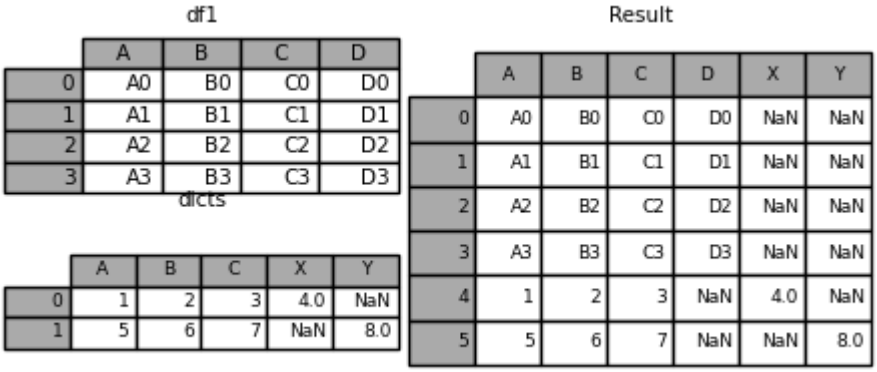


You should use `ignore_index` with this method to instruct DataFrame to discard its index. If you wish to preserve the index, you should construct an appropriately-indexed DataFrame and append or concatenate those objects.

You can also pass a list of dicts or Series:

```
In [37]: dicts = [{"A": 1, "B": 2, "C": 3, "X": 4}, {"A": 5, "B": 6, "C": 7, "Y": 8}]

In [38]: result = df1.append(dicts, ignore_index=True, sort=False)
```



2.7.2 Database-style DataFrame or named Series joining/merging

pandas has full-featured, **high performance** in-memory join operations idiomatically very similar to relational databases like SQL. These methods perform significantly better (in some cases well over an order of magnitude better) than other open source implementations (like `base::merge.data.frame` in R). The reason for this is careful algorithmic design and the internal layout of the data in `DataFrame`.

See the *cookbook* for some advanced strategies.

Users who are familiar with SQL but new to pandas might be interested in a *comparison with SQL*.

pandas provides a single function, *merge()*, as the entry point for all standard database join operations between DataFrame or named Series objects:

```
pd.merge(
    left,
    right,
    how="inner",
    on=None,
    left_on=None,
    right_on=None,
    left_index=False,
    right_index=False,
    sort=True,
    suffixes=("_x", "_y"),
    copy=True,
    indicator=False,
    validate=None,
)
```

- left: A DataFrame or named Series object.
- right: Another DataFrame or named Series object.
- on: Column or index level names to join on. Must be found in both the left and right DataFrame and/or Series objects. If not passed and left_index and right_index are False, the intersection of the columns in the DataFrames and/or Series will be inferred to be the join keys.
- left_on: Columns or index levels from the left DataFrame or Series to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the DataFrame or Series.
- right_on: Columns or index levels from the right DataFrame or Series to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the DataFrame or Series.
- left_index: If True, use the index (row labels) from the left DataFrame or Series as its join key(s). In the case of a DataFrame or Series with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame or Series.
- right_index: Same usage as left_index for the right DataFrame or Series
- how: One of 'left', 'right', 'outer', 'inner'. Defaults to inner. See below for more detailed description of each method.
- sort: Sort the result DataFrame by the join keys in lexicographical order. Defaults to True, setting to False will improve performance substantially in many cases.
- suffixes: A tuple of string suffixes to apply to overlapping columns. Defaults to ('_x', '_y').
- copy: Always copy data (default True) from the passed DataFrame or named Series objects, even when reindexing is not necessary. Cannot be avoided in many cases but may improve performance / memory usage. The cases where copying can be avoided are somewhat pathological but this option is provided nonetheless.
- indicator: Add a column to the output DataFrame called _merge with information on the source of each row. _merge is Categorical-type and takes on a value of left_only for observations whose merge key only appears in 'left' DataFrame or Series, right_only for observations whose merge key only appears in 'right' DataFrame or Series, and both if the observation's merge key is found in both.
- validate : string, default None. If specified, checks if merge is of specified type.
  - "one_to_one" or "1:1": checks if merge keys are unique in both left and right datasets.
  - "one_to_many" or "1:m": checks if merge keys are unique in left dataset.
  - "many_to_one" or "m:1": checks if merge keys are unique in right dataset.

- "many_to_many" or "m:m": allowed, but does not result in checks.

Note: Support for specifying index levels as the `on`, `left_on`, and `right_on` parameters was added in version 0.23.0. Support for merging named `Series` objects was added in version 0.24.0.

The return type will be the same as `left`. If `left` is a `DataFrame` or named `Series` and `right` is a subclass of `DataFrame`, the return type will still be `DataFrame`.

`merge` is a function in the pandas namespace, and it is also available as a `DataFrame` instance method *`merge()`*, with the calling `DataFrame` being implicitly considered the left object in the join.

The related *`join()`* method, uses `merge` internally for the index-on-index (by default) and column(s)-on-index join. If you are joining on index only, you may wish to use `DataFrame.join` to save yourself some typing.

Brief primer on merge methods (relational algebra)

Experienced users of relational databases like SQL will be familiar with the terminology used to describe join operations between two SQL-table like structures (`DataFrame` objects). There are several cases to consider which are very important to understand:

- **one-to-one** joins: for example when joining two `DataFrame` objects on their indexes (which must contain unique values).
- **many-to-one** joins: for example when joining an index (unique) to one or more columns in a different `DataFrame`.
- **many-to-many** joins: joining columns on columns.

Note: When joining columns on columns (potentially a many-to-many join), any indexes on the passed `DataFrame` objects **will be discarded**.

It is worth spending some time understanding the result of the **many-to-many** join case. In SQL / standard relational algebra, if a key combination appears more than once in both tables, the resulting table will have the **Cartesian product** of the associated data. Here is a very basic example with one unique key combination:

```
In [39]: left = pd.DataFrame(
   ....:     {
   ....:         "key": ["K0", "K1", "K2", "K3"],
   ....:         "A": ["A0", "A1", "A2", "A3"],
   ....:         "B": ["B0", "B1", "B2", "B3"],
   ....:     }
   ....: )
   ....:

In [40]: right = pd.DataFrame(
   ....:     {
   ....:         "key": ["K0", "K1", "K2", "K3"],
   ....:         "C": ["C0", "C1", "C2", "C3"],
   ....:         "D": ["D0", "D1", "D2", "D3"],
   ....:     }
   ....: )
   ....:

In [41]: result = pd.merge(left, right, on="key")
```

left

	key	A	B
0	K0	A0	B0
1	K1	A1	B1
2	K2	A2	B2
3	K3	A3	B3

right

	key	C	D
0	K0	C0	D0
1	K1	C1	D1
2	K2	C2	D2
3	K3	C3	D3

Result

	key	A	B	C	D
0	K0	A0	B0	C0	D0
1	K1	A1	B1	C1	D1
2	K2	A2	B2	C2	D2
3	K3	A3	B3	C3	D3

Here is a more complicated example with multiple join keys. Only the keys appearing in `left` and `right` are present (the intersection), since `how='inner'` by default.

```
In [42]: left = pd.DataFrame(
   ....:     {
   ....:         "key1": ["K0", "K0", "K1", "K2"],
   ....:         "key2": ["K0", "K1", "K0", "K1"],
   ....:         "A": ["A0", "A1", "A2", "A3"],
   ....:         "B": ["B0", "B1", "B2", "B3"],
   ....:     }
   ....: )
   ....:

In [43]: right = pd.DataFrame(
   ....:     {
   ....:         "key1": ["K0", "K1", "K1", "K2"],
   ....:         "key2": ["K0", "K0", "K0", "K0"],
   ....:         "C": ["C0", "C1", "C2", "C3"],
   ....:         "D": ["D0", "D1", "D2", "D3"],
   ....:     }
   ....: )
   ....:

In [44]: result = pd.merge(left, right, on=["key1", "key2"])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2

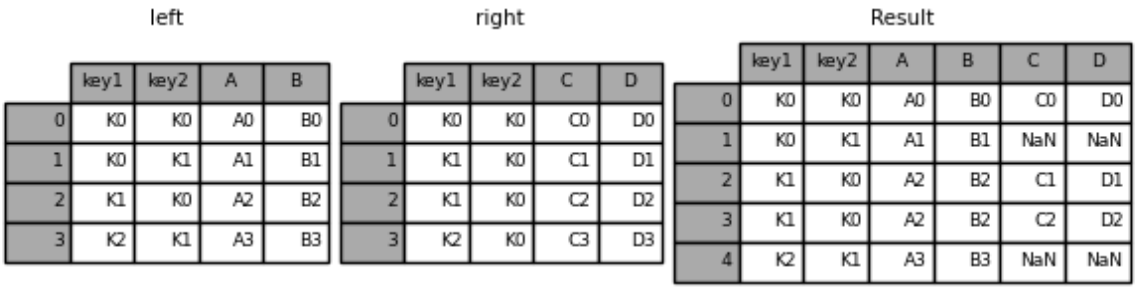
The `how` argument to `merge` specifies how to determine which keys are to be included in the resulting table. If a key combination **does not appear** in either the left or right tables, the values in the joined table will be `NA`. Here is a summary of the `how` options and their SQL equivalent names:

Merge method	SQL Join Name	Description
`left`	`LEFT OUTER JOIN`	Use keys from left frame only
`right`	`RIGHT OUTER JOIN`	Use keys from right frame only
`outer`	`FULL OUTER JOIN`	Use union of keys from both frames
`inner`	`INNER JOIN`	Use intersection of keys from both frames

```
In [45]: result = pd.merge(left, right, how="left", on=["key1", "key2"])
```

```

```



	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

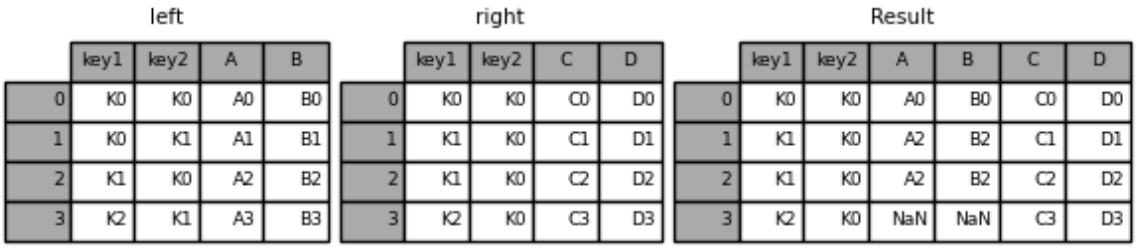
	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	C1	D1
3	K1	K0	A2	B2	C2	D2
4	K2	K1	A3	B3	NaN	NaN

```
In [46]: result = pd.merge(left, right, how="right", on=["key1", "key2"])
```

```

```



	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

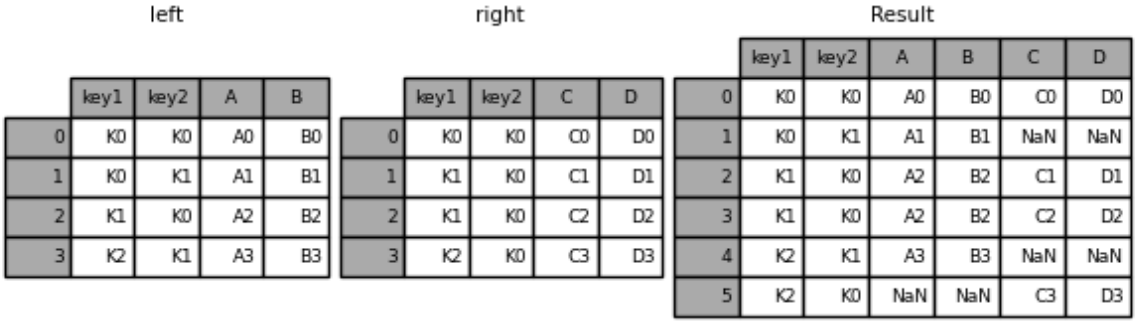
	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2
3	K2	K0	NaN	NaN	C3	D3

```
In [47]: result = pd.merge(left, right, how="outer", on=["key1", "key2"])
```

```

```



	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	C1	D1
3	K1	K0	A2	B2	C2	D2
4	K2	K1	A3	B3	NaN	NaN
5	K2	K0	NaN	NaN	C3	D3

```
In [48]: result = pd.merge(left, right, how="inner", on=["key1", "key2"])
```

left

	key1	key2	A	B
0	K0	K0	A0	B0
1	K0	K1	A1	B1
2	K1	K0	A2	B2
3	K2	K1	A3	B3

right

	key1	key2	C	D
0	K0	K0	C0	D0
1	K1	K0	C1	D1
2	K1	K0	C2	D2
3	K2	K0	C3	D3

Result

	key1	key2	A	B	C	D
0	K0	K0	A0	B0	C0	D0
1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	C2	D2

You can merge a mult-indexed Series and a DataFrame, if the names of the MultiIndex correspond to the columns from the DataFrame. Transform the Series to a DataFrame using *`Series.reset_index()`* before merging, as shown in the following example.

```
In [49]: df = pd.DataFrame({"Let": ["A", "B", "C"], "Num": [1, 2, 3]})

In [50]: df
Out[50]:
  Let  Num
0   A    1
1   B    2
2   C    3

In [51]: ser = pd.Series(
   ....:     ["a", "b", "c", "d", "e", "f"],
   ....:     index=pd.MultiIndex.from_arrays(
   ....:         [["A", "B", "C"] * 2, [1, 2, 3, 4, 5, 6]], names=["Let", "Num"]
   ....:     ),
   ....: )
   ....:

In [52]: ser
Out[52]:
Let  Num
A    1      a
B    2      b
C    3      c
A    4      d
B    5      e
C    6      f
dtype: object

In [53]: pd.merge(df, ser.reset_index(), on=["Let", "Num"])
Out[53]:
  Let  Num  0
0   A    1  a
1   B    2  b
2   C    3  c
```

Here is another example with duplicate join keys in DataFrames:

```
In [54]: left = pd.DataFrame({"A": [1, 2], "B": [2, 2]})

In [55]: right = pd.DataFrame({"A": [4, 5, 6], "B": [2, 2, 2]})
```

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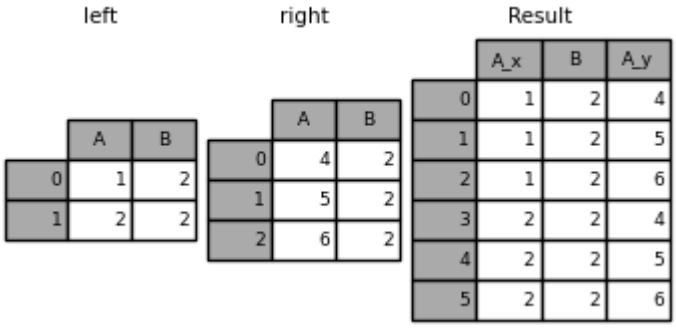
```
In [56]: result = pd.merge(left, right, on="B", how="outer")
```



	A	B
0	1	2
1	2	2

	A	B
0	4	2
1	5	2
2	6	2

	A_x	B	A_y
0	1	2	4
1	1	2	5
2	1	2	6
3	2	2	4
4	2	2	5
5	2	2	6

Warning: Joining / merging on duplicate keys can cause a returned frame that is the multiplication of the row dimensions, which may result in memory overflow. It is the user' s responsibility to manage duplicate values in keys before joining large DataFrames.

Checking for duplicate keys

Users can use the `validate` argument to automatically check whether there are unexpected duplicates in their merge keys. Key uniqueness is checked before merge operations and so should protect against memory overflows. Checking key uniqueness is also a good way to ensure user data structures are as expected.

In the following example, there are duplicate values of `B` in the right `DataFrame`. As this is not a one-to-one merge – as specified in the `validate` argument – an exception will be raised.

```
In [57]: left = pd.DataFrame({"A": [1, 2], "B": [1, 2]})

In [58]: right = pd.DataFrame({"A": [4, 5, 6], "B": [2, 2, 2]})
```

```
In [53]: result = pd.merge(left, right, on="B", how="outer", validate="one_to_one")
...
MergeError: Merge keys are not unique in right dataset; not a one-to-one merge
```

If the user is aware of the duplicates in the right `DataFrame` but wants to ensure there are no duplicates in the left DataFrame, one can use the `validate='one_to_many'` argument instead, which will not raise an exception.

```
In [59]: pd.merge(left, right, on="B", how="outer", validate="one_to_many")
Out[59]:
   A_x  B  A_y
0    1  1  NaN
1    2  2  4.0
2    2  2  5.0
3    2  2  6.0
```

The merge indicator

merge() accepts the argument `indicator`. If `True`, a Categorical-type column called `_merge` will be added to the output object that takes on values:

Observation Origin	`_merge` value
Merge key only in `'left'` frame	`left_only`
Merge key only in `'right'` frame	`right_only`
Merge key in both frames	`both`

```
In [60]: df1 = pd.DataFrame({"col1": [0, 1], "col_left": ["a", "b"]})

In [61]: df2 = pd.DataFrame({"col1": [1, 2, 2], "col_right": [2, 2, 2]})

In [62]: pd.merge(df1, df2, on="col1", how="outer", indicator=True)
Out[62]:
   col1 col_left  col_right      _merge
0     0        a        NaN   left_only
1     1        b        2.0        both
2     2      NaN        2.0  right_only
3     2      NaN        2.0  right_only
```

The `indicator` argument will also accept string arguments, in which case the indicator function will use the value of the passed string as the name for the indicator column.

```
In [63]: pd.merge(df1, df2, on="col1", how="outer", indicator="indicator_column")
Out[63]:
   col1 col_left  col_right indicator_column
0     0        a        NaN        left_only
1     1        b        2.0             both
2     2      NaN        2.0       right_only
3     2      NaN        2.0       right_only
```

Merge dtypes

Merging will preserve the dtype of the join keys.

```
In [64]: left = pd.DataFrame({"key": [1], "v1": [10]})

In [65]: left
Out[65]:
   key  v1
0    1  10

In [66]: right = pd.DataFrame({"key": [1, 2], "v1": [20, 30]})

In [67]: right
Out[67]:
   key  v1
0    1  20
1    2  30
```

We are able to preserve the join keys:

```
In [68]: pd.merge(left, right, how="outer")
Out[68]:
   key  v1
0    1  10
1    1  20
2    2  30

In [69]: pd.merge(left, right, how="outer").dtypes
Out[69]:
key    int64
v1     int64
dtype: object
```

Of course if you have missing values that are introduced, then the resulting dtype will be upcast.

```
In [70]: pd.merge(left, right, how="outer", on="key")
Out[70]:
   key  v1_x  v1_y
0    1  10.0    20
1    2   NaN    30

In [71]: pd.merge(left, right, how="outer", on="key").dtypes
Out[71]:
key       int64
v1_x    float64
v1_y      int64
dtype: object
```

Merging will preserve `category` dtypes of the mergands. See also the section on *categoricals*.

The left frame.

```
In [72]: from pandas.api.types import CategoricalDtype

In [73]: X = pd.Series(np.random.choice(["foo", "bar"], size=(10,)))

In [74]: X = X.astype(CategoricalDtype(categories=["foo", "bar"]))

In [75]: left = pd.DataFrame(
   ....:     {"X": X, "Y": np.random.choice(["one", "two", "three"], size=(10,))}
   ....: )
   ....:

In [76]: left
Out[76]:
     X      Y
0  bar    one
1  foo    one
2  foo  three
3  bar  three
4  foo    one
5  bar    one
6  bar  three
7  bar  three
8  bar  three
9  foo  three

In [77]: left.dtypes
```

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```
Out[77]:
X    category
Y      object
dtype: object
```

The right frame.

```
In [78]: right = pd.DataFrame(
   ....:     {
   ....:         "X": pd.Series(["foo", "bar"], dtype=CategoricalDtype(["foo", "bar
↪"])),
   ....:         "Z": [1, 2],
   ....:     }
   ....: )
   ....:

In [79]: right
Out[79]:
     X  Z
0  foo  1
1  bar  2

In [80]: right.dtypes
Out[80]:
X    category
Z       int64
dtype: object
```

The merged result:

```
In [81]: result = pd.merge(left, right, how="outer")

In [82]: result
Out[82]:
     X      Y  Z
0  bar    one  2
1  bar  three  2
2  bar    one  2
3  bar  three  2
4  bar  three  2
5  bar  three  2
6  foo    one  1
7  foo  three  1
8  foo    one  1
9  foo  three  1

In [83]: result.dtypes
Out[83]:
X    category
Y      object
Z       int64
dtype: object
```

Note: The category dtypes must be *exactly* the same, meaning the same categories and the ordered attribute. Otherwise the result will coerce to the categories' dtype.

Note: Merging on `category` dtypes that are the same can be quite performant compared to `object` dtype merging.

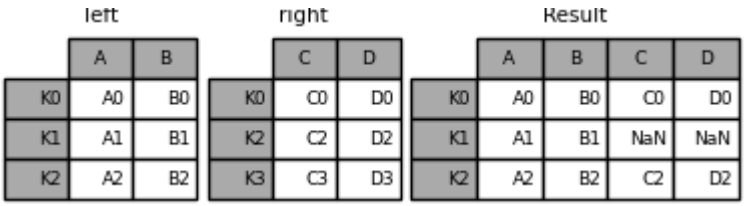
Joining on index

`DataFrame.join()` is a convenient method for combining the columns of two potentially differently-indexed `DataFrames` into a single result `DataFrame`. Here is a very basic example:

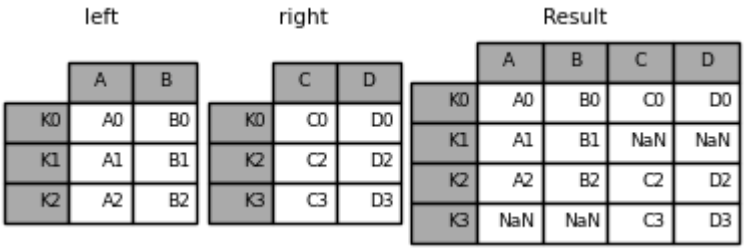
```
In [84]: left = pd.DataFrame(
   ....:     {"A": ["A0", "A1", "A2"], "B": ["B0", "B1", "B2"]}, index=["K0", "K1",
↪"K2"]
   ....: )
   ....:

In [85]: right = pd.DataFrame(
   ....:     {"C": ["C0", "C2", "C3"], "D": ["D0", "D2", "D3"]}, index=["K0", "K2",
↪"K3"]
   ....: )
   ....:

In [86]: result = left.join(right)
```

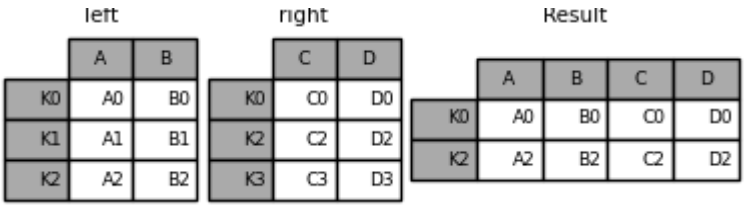



```
In [87]: result = left.join(right, how="outer")
```



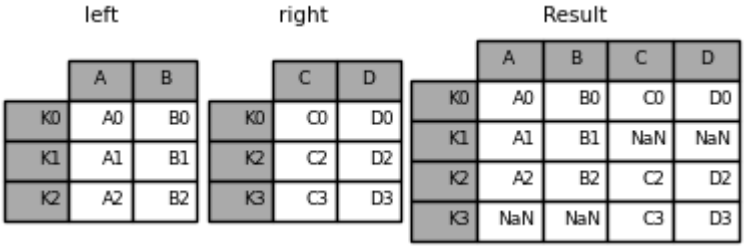
The same as above, but with `how='inner'`.

```
In [88]: result = left.join(right, how="inner")
```

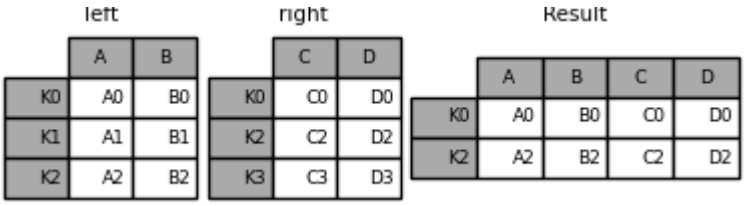


The data alignment here is on the indexes (row labels). This same behavior can be achieved using `merge` plus additional arguments instructing it to use the indexes:

```
In [89]: result = pd.merge(left, right, left_index=True, right_index=True, how="outer
↪")
```




```
In [90]: result = pd.merge(left, right, left_index=True, right_index=True, how="inner
↪")
```



Joining key columns on an index

join() takes an optional `on` argument which may be a column or multiple column names, which specifies that the passed `DataFrame` is to be aligned on that column in the `DataFrame`. These two function calls are completely equivalent:

```
left.join(right, on=key_or_keys)
pd.merge(
    left, right, left_on=key_or_keys, right_index=True, how="left", sort=False
)
```

Obviously you can choose whichever form you find more convenient. For many-to-one joins (where one of the `DataFrame`'s is already indexed by the join key), using `join` may be more convenient. Here is a simple example:

```
In [91]: left = pd.DataFrame(
   ....:     {
   ....:         "A": ["A0", "A1", "A2", "A3"],
   ....:         "B": ["B0", "B1", "B2", "B3"],
```

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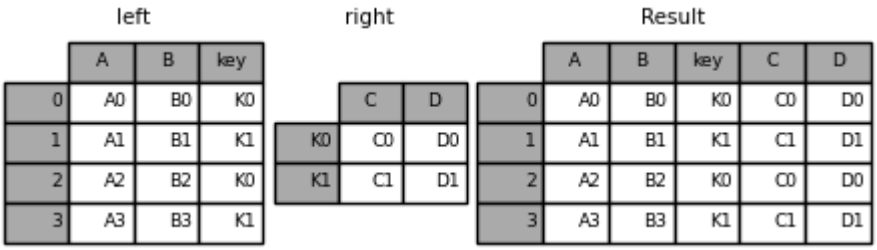
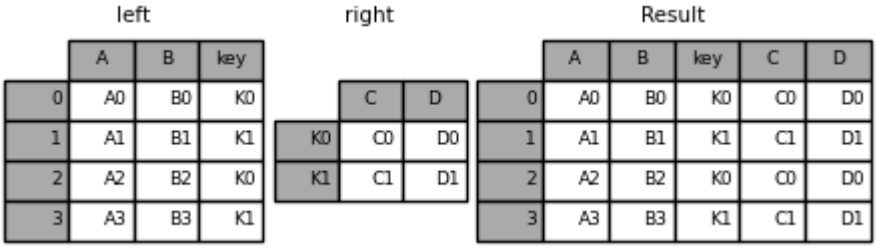
```
   ....:         "key": ["K0", "K1", "K0", "K1"],
   ....:     }
   ....: )
   ....:

In [92]: right = pd.DataFrame({"C": ["C0", "C1"], "D": ["D0", "D1"]}, index=["K0", "K1
↪"])

In [93]: result = left.join(right, on="key")
```




```
In [94]: result = pd.merge(
   ....:     left, right, left_on="key", right_index=True, how="left", sort=False
   ....: )
   ....:
```



To join on multiple keys, the passed DataFrame must have a `MultiIndex`:

```
In [95]: left = pd.DataFrame(
   ....:     {
   ....:         "A": ["A0", "A1", "A2", "A3"],
   ....:         "B": ["B0", "B1", "B2", "B3"],
   ....:         "key1": ["K0", "K0", "K1", "K2"],
   ....:         "key2": ["K0", "K1", "K0", "K1"],
   ....:     }
   ....: )
   ....:

In [96]: index = pd.MultiIndex.from_tuples(
   ....:     [("K0", "K0"), ("K1", "K0"), ("K2", "K0"), ("K2", "K1")]
   ....: )
   ....:

In [97]: right = pd.DataFrame(
   ....:     {"C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]},␣
↪index=index
```

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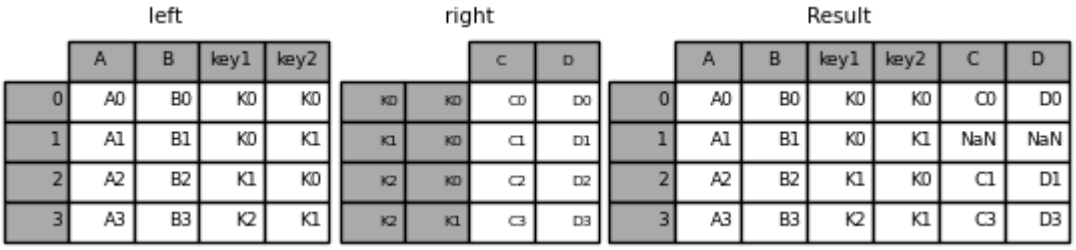
```
   ....: )
   ....:
```

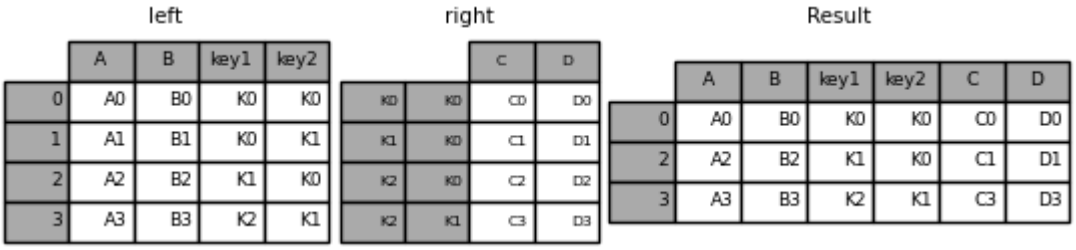
Now this can be joined by passing the two key column names:

```
In [98]: result = left.join(right, on=["key1", "key2"])
```



The default for `DataFrame.join` is to perform a left join (essentially a "VLOOKUP" operation, for Excel users), which uses only the keys found in the calling DataFrame. Other join types, for example inner join, can be just as easily performed:

```
In [99]: result = left.join(right, on=["key1", "key2"], how="inner")
```



As you can see, this drops any rows where there was no match.

Joining a single Index to a MultiIndex

You can join a singly-indexed `DataFrame` with a level of a MultiIndexed `DataFrame`. The level will match on the name of the index of the singly-indexed frame against a level name of the MultiIndexed frame.

```
In [100]: left = pd.DataFrame(
   .....:     {"A": ["A0", "A1", "A2"], "B": ["B0", "B1", "B2"]},
   .....:     index=pd.Index(["K0", "K1", "K2"], name="key"),
   .....: )
   .....:

In [101]: index = pd.MultiIndex.from_tuples(
   .....:     [("K0", "Y0"), ("K1", "Y1"), ("K2", "Y2"), ("K2", "Y3")],
   .....:     names=["key", "Y"],
   .....: )
   .....:
```

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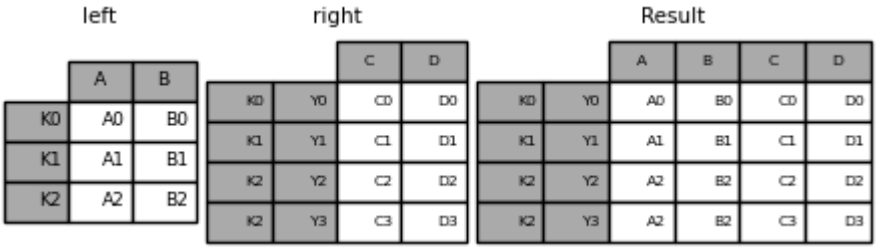
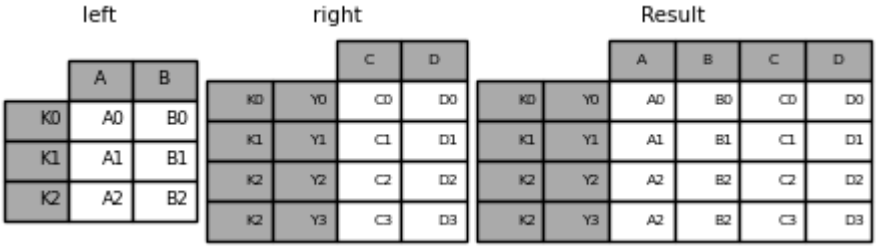
```
In [102]: right = pd.DataFrame(
   .....:     {"C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]},
   .....:     index=index,
   .....: )
   .....:

In [103]: result = left.join(right, how="inner")
```



This is equivalent but less verbose and more memory efficient / faster than this.

```
In [104]: result = pd.merge(
   .....:     left.reset_index(), right.reset_index(), on=["key"], how="inner"
   .....: ).set_index(["key","Y"])
   .....:
```



Joining with two MultiIndexes

This is supported in a limited way, provided that the index for the right argument is completely used in the join, and is a subset of the indices in the left argument, as in this example:

```
In [105]: leftindex = pd.MultiIndex.from_product(
   .....:     [list("abc"), list("xy"), [1, 2]], names=["abc", "xy", "num"]
   .....: )
   .....:

In [106]: left = pd.DataFrame({"v1": range(12)}, index=leftindex)

In [107]: left
Out[107]:
             v1
abc xy num
a   x  1      0
```

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```
        2     1
    y   1     2
        2     3
b   x   1     4
        2     5
    y   1     6
        2     7
c   x   1     8
        2     9
    y   1    10
        2    11

In [108]: rightindex = pd.MultiIndex.from_product(
   .....:     [list("abc"), list("xy")], names=["abc", "xy"]
   .....: )
   .....:

In [109]: right = pd.DataFrame({"v2": [100 * i for i in range(1, 7)]},␣
↪index=rightindex)

In [110]: right
Out[110]:
         v2
abc xy
a   x   100
    y   200
b   x   300
    y   400
c   x   500
    y   600

In [111]: left.join(right, on=["abc", "xy"], how="inner")
Out[111]:
            v1   v2
abc xy num
a   x  1     0  100
       2     1  100
    y  1     2  200
       2     3  200
b   x  1     4  300
       2     5  300
    y  1     6  400
       2     7  400
c   x  1     8  500
       2     9  500
    y  1    10  600
       2    11  600
```

If that condition is not satisfied, a join with two multi-indexes can be done using the following code.

```
In [112]: leftindex = pd.MultiIndex.from_tuples(
   .....:     [("K0", "X0"), ("K0", "X1"), ("K1", "X2")], names=["key", "X"]
   .....: )
   .....:

In [113]: left = pd.DataFrame(
   .....:     {"A": ["A0", "A1", "A2"], "B": ["B0", "B1", "B2"]}, index=leftindex
```

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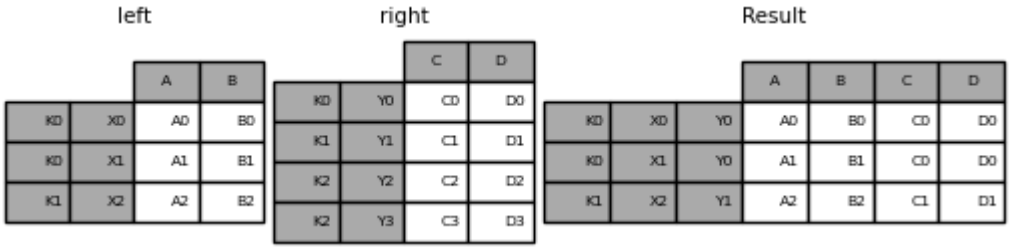
```
   .....: )
   .....:

In [114]: rightindex = pd.MultiIndex.from_tuples(
   .....:     [("K0", "Y0"), ("K1", "Y1"), ("K2", "Y2"), ("K2", "Y3")], names=["key",
↪"Y"]
   .....: )
   .....:

In [115]: right = pd.DataFrame(
   .....:     {"C": ["C0", "C1", "C2", "C3"], "D": ["D0", "D1", "D2", "D3"]},␣
↪index=rightindex
   .....: )
   .....:

In [116]: result = pd.merge(
   .....:     left.reset_index(), right.reset_index(), on=["key"], how="inner"
   .....: ).set_index(["key", "X", "Y"])
   .....:
```



Merging on a combination of columns and index levels

Strings passed as the `on`, `left_on`, and `right_on` parameters may refer to either column names or index level names. This enables merging `DataFrame` instances on a combination of index levels and columns without resetting indexes.

```
In [117]: left_index = pd.Index(["K0", "K0", "K1", "K2"], name="key1")

In [118]: left = pd.DataFrame(
   .....:     {
   .....:         "A": ["A0", "A1", "A2", "A3"],
   .....:         "B": ["B0", "B1", "B2", "B3"],
   .....:         "key2": ["K0", "K1", "K0", "K1"],
   .....:     },
   .....:     index=left_index,
   .....: )
   .....:

In [119]: right_index = pd.Index(["K0", "K1", "K2", "K2"], name="key1")

In [120]: right = pd.DataFrame(
   .....:     {
   .....:         "C": ["C0", "C1", "C2", "C3"],
```

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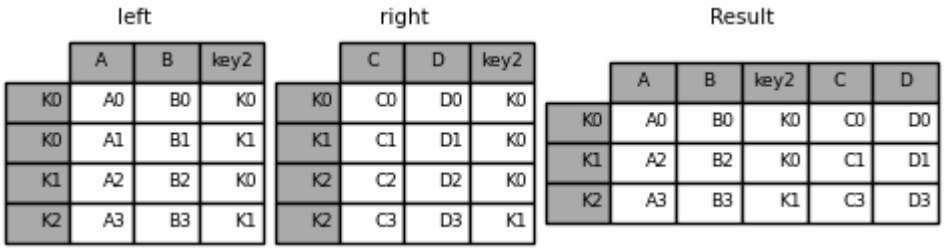
```
   .....:             "D": ["D0", "D1", "D2", "D3"],
   .....:             "key2": ["K0", "K0", "K0", "K1"],
   .....:         },
   .....:         index=right_index,
   .....: )
   .....:

In [121]: result = left.merge(right, on=["key1", "key2"])
```



	A	B	key2
K0	A0	B0	K0
K0	A1	B1	K1
K1	A2	B2	K0
K2	A3	B3	K1

	C	D	key2
K0	C0	D0	K0
K1	C1	D1	K0
K2	C2	D2	K0
K2	C3	D3	K1

	A	B	key2	C	D
K0	A0	B0	K0	C0	D0
K1	A2	B2	K0	C1	D1
K2	A3	B3	K1	C3	D3

Note: When DataFrames are merged on a string that matches an index level in both frames, the index level is preserved as an index level in the resulting DataFrame.

Note: When DataFrames are merged using only some of the levels of a `MultiIndex`, the extra levels will be dropped from the resulting merge. In order to preserve those levels, use `reset_index` on those level names to move those levels to columns prior to doing the merge.

Note: If a string matches both a column name and an index level name, then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

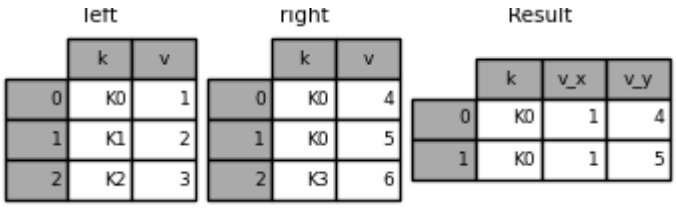
Overlapping value columns

The merge `suffixes` argument takes a tuple of list of strings to append to overlapping column names in the input `DataFrame`s to disambiguate the result columns:

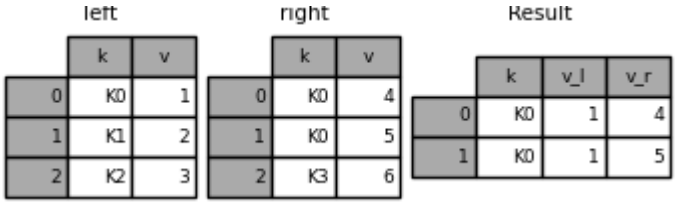
```
In [122]: left = pd.DataFrame({"k": ["K0", "K1", "K2"], "v": [1, 2, 3]})

In [123]: right = pd.DataFrame({"k": ["K0", "K0", "K3"], "v": [4, 5, 6]})

In [124]: result = pd.merge(left, right, on="k")
```




```
In [125]: result = pd.merge(left, right, on="k", suffixes=("_l", "_r"))
```

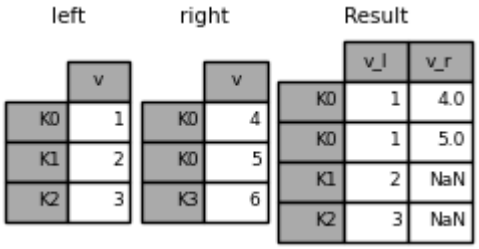


DataFrame.join() has `lsuffix` and `rsuffix` arguments which behave similarly.

```
In [126]: left = left.set_index("k")

In [127]: right = right.set_index("k")

In [128]: result = left.join(right, lsuffix="_l", rsuffix="_r")
```



Joining multiple DataFrames

A list or tuple of `DataFrames` can also be passed to *join()* to join them together on their indexes.

```
In [129]: right2 = pd.DataFrame({"v": [7, 8, 9]}, index=["K1", "K1", "K2"])

In [130]: result = left.join([right, right2])
```

left

	v
K0	1
K1	2
K2	3

right

	v
K0	4
K0	5
K3	6

right2

	v
K1	7
K1	8
K2	9

Result

	v_x	v_y	v
K0	1	4.0	NaN
K0	1	5.0	NaN
K1	2	NaN	7.0
K1	2	NaN	8.0
K2	3	NaN	9.0

Merging together values within Series or DataFrame columns

Another fairly common situation is to have two like-indexed (or similarly indexed) `Series` or `DataFrame` objects and wanting to "patch" values in one object from values for matching indices in the other. Here is an example:

```
In [131]: df1 = pd.DataFrame(
   .....:     [[np.nan, 3.0, 5.0], [-4.6, np.nan, np.nan], [np.nan, 7.0, np.nan]]
   .....: )
   .....:

In [132]: df2 = pd.DataFrame([[-42.6, np.nan, -8.2], [-5.0, 1.6, 4]], index=[1, 2])
```

For this, use the *`combine_first()`* method:

```
In [133]: result = df1.combine_first(df2)
```

```

```

df1

	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	NaN
2	NaN	7.0	NaN

df2

	0	1	2
1	-42.6	NaN	-8.2
2	-5.0	1.6	4.0

Result

	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	-8.2
2	-5.0	7.0	4.0

Note that this method only takes values from the right `DataFrame` if they are missing in the left `DataFrame`. A related method, *`update()`*, alters non-NA values in place:

```
In [134]: df1.update(df2)
```

```

```

df1

	0	1	2
0	NaN	3.0	5.0
1	-4.6	NaN	NaN
2	NaN	7.0	NaN

df2

	0	1	2
1	-42.6	NaN	-8.2
2	-5.0	1.6	4.0

Result

	0	1	2
0	NaN	3.0	5.0
1	-42.6	NaN	-8.2
2	-5.0	1.6	4.0

2.7.3 Timeseries friendly merging

Merging ordered data

A *merge_ordered()* function allows combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```
In [135]: left = pd.DataFrame(
   .....:     {"k": ["K0", "K1", "K1", "K2"], "lv": [1, 2, 3, 4], "s": ["a", "b", "c",
↪ "d"]}
   .....: )
   .....:

In [136]: right = pd.DataFrame({"k": ["K1", "K2", "K4"], "rv": [1, 2, 3]})

In [137]: pd.merge_ordered(left, right, fill_method="ffill", left_by="s")
Out[137]:
     k   lv  s   rv
0   K0  1.0  a  NaN
1   K1  1.0  a  1.0
2   K2  1.0  a  2.0
3   K4  1.0  a  3.0
4   K1  2.0  b  1.0
5   K2  2.0  b  2.0
6   K4  2.0  b  3.0
7   K1  3.0  c  1.0
8   K2  3.0  c  2.0
9   K4  3.0  c  3.0
10  K1  NaN  d  1.0
11  K2  4.0  d  2.0
12  K4  4.0  d  3.0
```

Merging asof

A *merge_asof()* is similar to an ordered left-join except that we match on nearest key rather than equal keys. For each row in the `left` `DataFrame`, we select the last row in the `right` `DataFrame` whose `on` key is less than the left's key. Both DataFrames must be sorted by the key.

Optionally an asof merge can perform a group-wise merge. This matches the `by` key equally, in addition to the nearest match on the `on` key.

For example; we might have `trades` and `quotes` and we want to `asof` merge them.

```
In [138]: trades = pd.DataFrame(
   .....:     {
   .....:         "time": pd.to_datetime(
   .....:             [
   .....:                 "20160525 13:30:00.023",
   .....:                 "20160525 13:30:00.038",
   .....:                 "20160525 13:30:00.048",
   .....:                 "20160525 13:30:00.048",
   .....:                 "20160525 13:30:00.048",
   .....:             ]
   .....:         ),
   .....:         "ticker": ["MSFT", "MSFT", "GOOG", "GOOG", "AAPL"],
   .....:         "price": [51.95, 51.95, 720.77, 720.92, 98.00],
```

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```
   .....:         "quantity": [75, 155, 100, 100, 100],
   .....:     },
   .....:     columns=["time", "ticker", "price", "quantity"],
   .....: )
   .....:

In [139]: quotes = pd.DataFrame(
   .....:     {
   .....:         "time": pd.to_datetime(
   .....:             [
   .....:                 "20160525 13:30:00.023",
   .....:                 "20160525 13:30:00.023",
   .....:                 "20160525 13:30:00.030",
   .....:                 "20160525 13:30:00.041",
   .....:                 "20160525 13:30:00.048",
   .....:                 "20160525 13:30:00.049",
   .....:                 "20160525 13:30:00.072",
   .....:                 "20160525 13:30:00.075",
   .....:             ]
   .....:         ),
   .....:         "ticker": ["GOOG", "MSFT", "MSFT", "MSFT", "GOOG", "AAPL", "GOOG",
↪"MSFT"],
   .....:         "bid": [720.50, 51.95, 51.97, 51.99, 720.50, 97.99, 720.50, 52.01],
   .....:         "ask": [720.93, 51.96, 51.98, 52.00, 720.93, 98.01, 720.88, 52.03],
   .....:     },
   .....:     columns=["time", "ticker", "bid", "ask"],
   .....: )
   .....:
```

```
In [140]: trades
Out[140]:
                     time ticker   price  quantity
0 2016-05-25 13:30:00.023   MSFT   51.95        75
1 2016-05-25 13:30:00.038   MSFT   51.95       155
2 2016-05-25 13:30:00.048   GOOG  720.77       100
3 2016-05-25 13:30:00.048   GOOG  720.92       100
4 2016-05-25 13:30:00.048   AAPL   98.00       100

In [141]: quotes
Out[141]:
                     time ticker     bid     ask
0 2016-05-25 13:30:00.023   GOOG  720.50  720.93
1 2016-05-25 13:30:00.023   MSFT   51.95   51.96
2 2016-05-25 13:30:00.030   MSFT   51.97   51.98
3 2016-05-25 13:30:00.041   MSFT   51.99   52.00
4 2016-05-25 13:30:00.048   GOOG  720.50  720.93
5 2016-05-25 13:30:00.049   AAPL   97.99   98.01
6 2016-05-25 13:30:00.072   GOOG  720.50  720.88
7 2016-05-25 13:30:00.075   MSFT   52.01   52.03
```

By default we are taking the asof of the quotes.

```
In [142]: pd.merge_asof(trades, quotes, on="time", by="ticker")
Out[142]:
                     time ticker   price  quantity     bid     ask
0 2016-05-25 13:30:00.023   MSFT   51.95        75   51.95   51.96
```

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```
1 2016-05-25 13:30:00.038   MSFT   51.95       155   51.97   51.98
2 2016-05-25 13:30:00.048   GOOG  720.77       100  720.50  720.93
3 2016-05-25 13:30:00.048   GOOG  720.92       100  720.50  720.93
4 2016-05-25 13:30:00.048   AAPL   98.00       100     NaN     NaN
```

We only asof within `2ms` between the quote time and the trade time.

```
In [143]: pd.merge_asof(trades, quotes, on="time", by="ticker", tolerance=pd.
↪Timedelta("2ms"))
Out[143]:
                     time ticker   price  quantity     bid     ask
0 2016-05-25 13:30:00.023   MSFT   51.95        75   51.95   51.96
1 2016-05-25 13:30:00.038   MSFT   51.95       155     NaN     NaN
2 2016-05-25 13:30:00.048   GOOG  720.77       100  720.50  720.93
3 2016-05-25 13:30:00.048   GOOG  720.92       100  720.50  720.93
4 2016-05-25 13:30:00.048   AAPL   98.00       100     NaN     NaN
```

We only asof within `10ms` between the quote time and the trade time and we exclude exact matches on time. Note that though we exclude the exact matches (of the quotes), prior quotes **do** propagate to that point in time.

```
In [144]: pd.merge_asof(
   .....:     trades,
   .....:     quotes,
   .....:     on="time",
   .....:     by="ticker",
   .....:     tolerance=pd.Timedelta("10ms"),
   .....:     allow_exact_matches=False,
   .....: )
   .....:
Out[144]:
                     time ticker   price  quantity    bid    ask
0 2016-05-25 13:30:00.023   MSFT   51.95        75    NaN    NaN
1 2016-05-25 13:30:00.038   MSFT   51.95       155  51.97  51.98
2 2016-05-25 13:30:00.048   GOOG  720.77       100    NaN    NaN
3 2016-05-25 13:30:00.048   GOOG  720.92       100    NaN    NaN
4 2016-05-25 13:30:00.048   AAPL   98.00       100    NaN    NaN
```

2.7.4 Comparing objects

The *compare()* and *compare()* methods allow you to compare two DataFrame or Series, respectively, and summarize their differences.

This feature was added in *V1.1.0*.

For example, you might want to compare two `DataFrame` and stack their differences side by side.

```
In [145]: df = pd.DataFrame(
   .....:     {
   .....:         "col1": ["a", "a", "b", "b", "a"],
   .....:         "col2": [1.0, 2.0, 3.0, np.nan, 5.0],
   .....:         "col3": [1.0, 2.0, 3.0, 4.0, 5.0],
   .....:     },
   .....:     columns=["col1", "col2", "col3"],
   .....: )
   .....:
```

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```
In [146]: df
Out[146]:
  col1  col2  col3
0    a   1.0   1.0
1    a   2.0   2.0
2    b   3.0   3.0
3    b   NaN   4.0
4    a   5.0   5.0
```

```
In [147]: df2 = df.copy()

In [148]: df2.loc[0, "col1"] = "c"

In [149]: df2.loc[2, "col3"] = 4.0

In [150]: df2
Out[150]:
  col1  col2  col3
0    c   1.0   1.0
1    a   2.0   2.0
2    b   3.0   4.0
3    b   NaN   4.0
4    a   5.0   5.0
```

```
In [151]: df.compare(df2)
Out[151]:
  col1       col3
  self other self other
0    a     c  NaN   NaN
2  NaN   NaN  3.0   4.0
```

By default, if two corresponding values are equal, they will be shown as `NaN`. Furthermore, if all values in an entire row / column, the row / column will be omitted from the result. The remaining differences will be aligned on columns.

If you wish, you may choose to stack the differences on rows.

```
In [152]: df.compare(df2, align_axis=0)
Out[152]:
        col1  col3
0 self     a   NaN
  other    c   NaN
2 self   NaN   3.0
  other  NaN   4.0
```

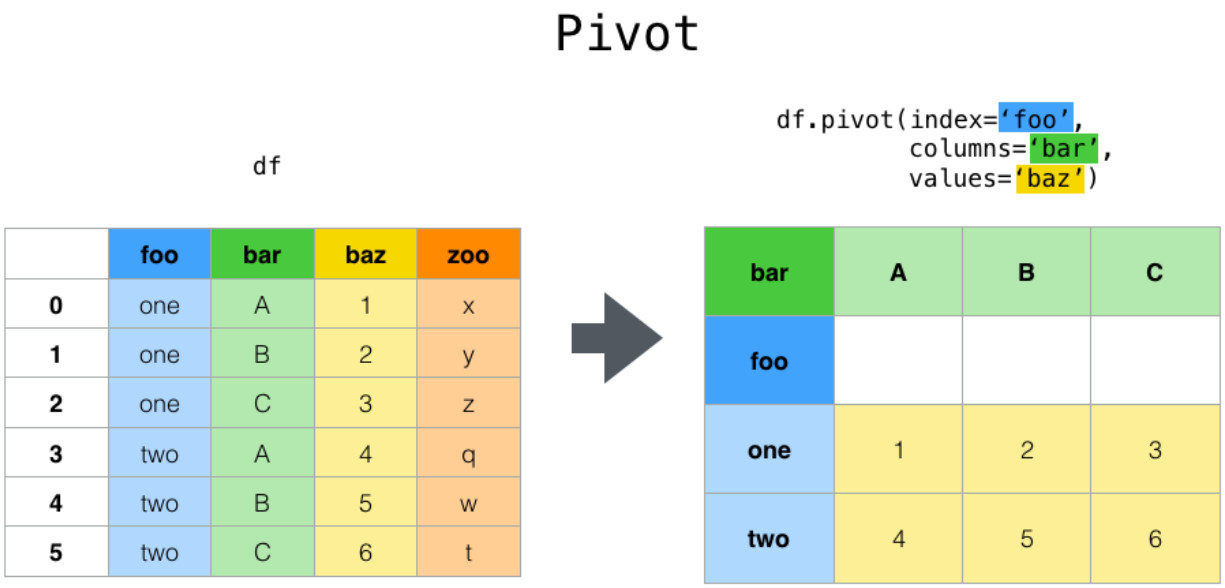
If you wish to keep all original rows and columns, set `keep_shape` argument to `True`.

```
In [153]: df.compare(df2, keep_shape=True)
Out[153]:
  col1       col2       col3
  self other self other self other
0    a     c  NaN   NaN  NaN   NaN
1  NaN   NaN  NaN   NaN  NaN   NaN
2  NaN   NaN  NaN   NaN  3.0   4.0
3  NaN   NaN  NaN   NaN  NaN   NaN
4  NaN   NaN  NaN   NaN  NaN   NaN
```

You may also keep all the original values even if they are equal.

2.8 Reshaping and pivot tables

2.8.1 Reshaping by pivoting DataFrame objects



	foo	bar	baz	zoo
0	one	A	1	x
1	one	B	2	y
2	one	C	3	z
3	two	A	4	q
4	two	B	5	w
5	two	C	6	t

bar	A	B	C
foo			
one	1	2	3
two	4	5	6

Data is often stored in so-called "stacked" or "record" format:

```
In [1]: df
Out[1]:
          date variable     value
0   2000-01-03        A  0.469112
1   2000-01-04        A -0.282863
2   2000-01-05        A -1.509059
3   2000-01-03        B -1.135632
4   2000-01-04        B  1.212112
5   2000-01-05        B -0.173215
6   2000-01-03        C  0.119209
7   2000-01-04        C -1.044236
8   2000-01-05        C -0.861849
9   2000-01-03        D -2.104569
10  2000-01-04        D -0.494929
11  2000-01-05        D  1.071804
```

For the curious here is how the above `DataFrame` was created:

```
import pandas._testing as tm


def unpivot(frame):
    N, K = frame.shape
    data = {
```

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```
        "value": frame.to_numpy().ravel("F"),
        "variable": np.asarray(frame.columns).repeat(N),
        "date": np.tile(np.asarray(frame.index), K),
    }
    return pd.DataFrame(data, columns=["date", "variable", "value"])


df = unpivot(tm.makeTimeDataFrame(3))
```

To select out everything for variable `A` we could do:

```
In [2]: df[df["variable"] == "A"]
Out[2]:
        date variable     value
0 2000-01-03        A  0.469112
1 2000-01-04        A -0.282863
2 2000-01-05        A -1.509059
```

But suppose we wish to do time series operations with the variables. A better representation would be where the `columns` are the unique variables and an `index` of dates identifies individual observations. To reshape the data into this form, we use the *`DataFrame.pivot()`* method (also implemented as a top level function *`pivot()`*):

```
In [3]: df.pivot(index="date", columns="variable", values="value")
Out[3]:
variable           A         B         C         D
date
2000-01-03  0.469112 -1.135632  0.119209 -2.104569
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804
```

If the `values` argument is omitted, and the input `DataFrame` has more than one column of values which are not used as column or index inputs to `pivot`, then the resulting "pivoted" `DataFrame` will have *hierarchical columns* whose topmost level indicates the respective value column:

```
In [4]: df["value2"] = df["value"] * 2

In [5]: pivoted = df.pivot(index="date", columns="variable")

In [6]: pivoted
Out[6]:
               value                                     value2
↪
variable           A         B         C         D         A         B         C
↪    D
date
↪
2000-01-03  0.469112 -1.135632  0.119209 -2.104569  0.938225 -2.271265  0.238417 -4.
↪209138
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929 -0.565727  2.424224 -2.088472 -0.
↪989859
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804 -3.018117 -0.346429 -1.723698  2.
↪143608
```

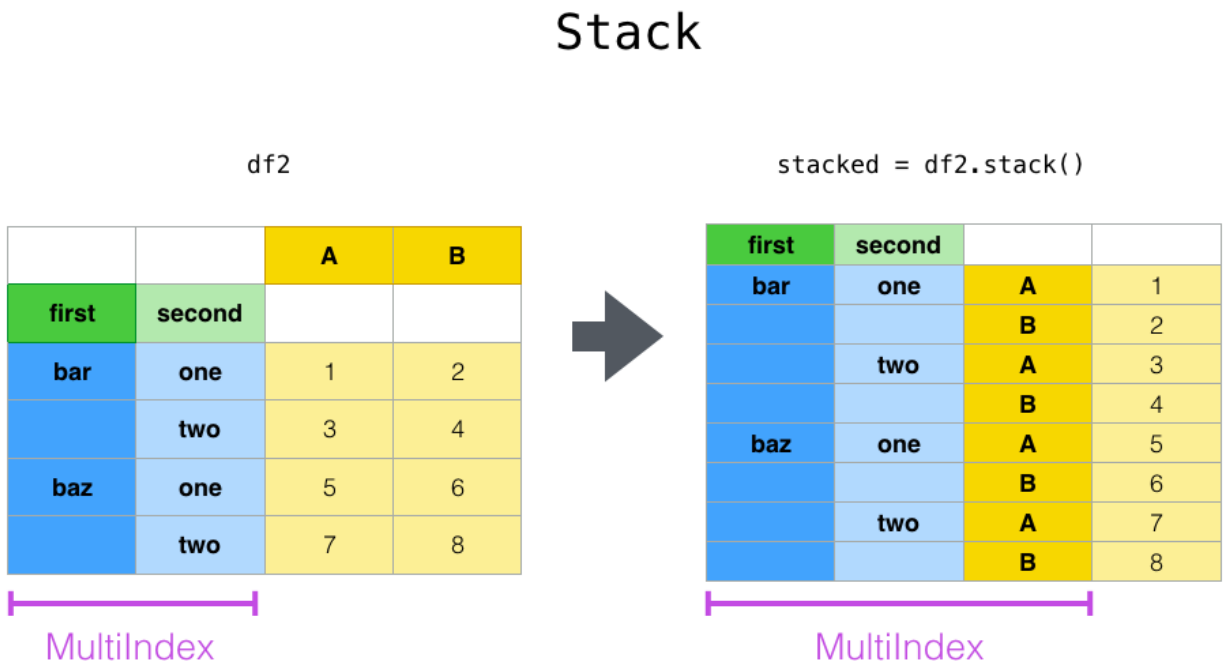
You can then select subsets from the pivoted `DataFrame`:

```
In [7]: pivoted["value2"]
Out[7]:
variable            A         B         C         D
date
2000-01-03  0.938225 -2.271265  0.238417 -4.209138
2000-01-04 -0.565727  2.424224 -2.088472 -0.989859
2000-01-05 -3.018117 -0.346429 -1.723698  2.143608
```

Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

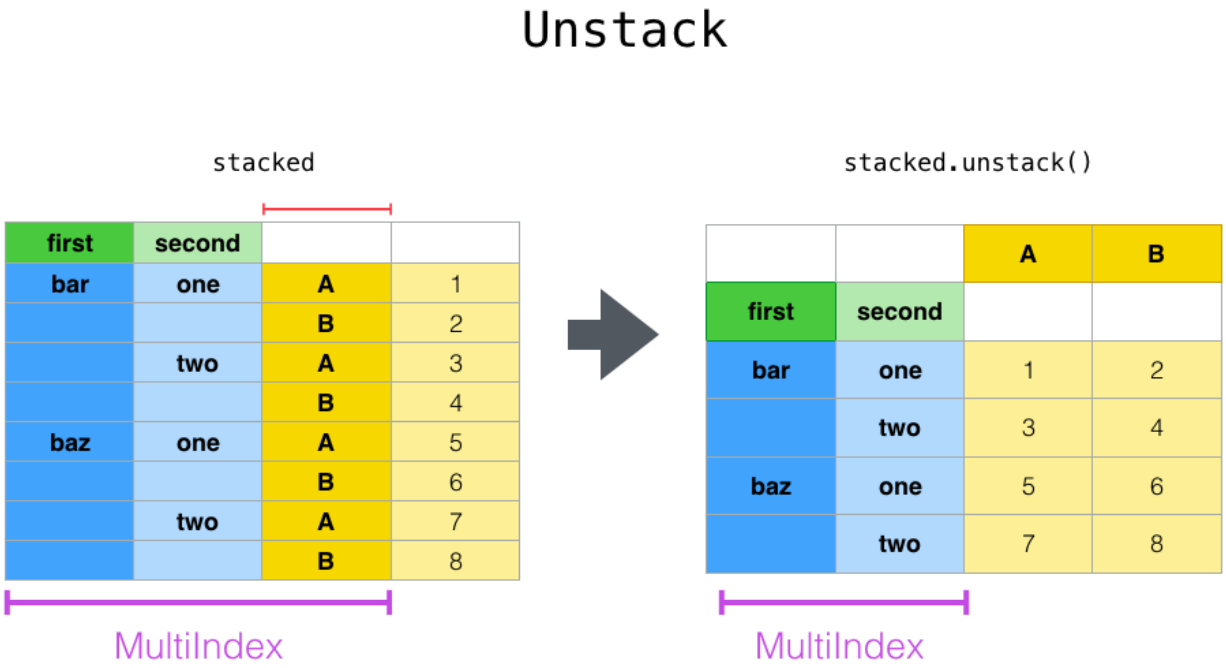
Note: *pivot()* will error with a `ValueError: Index contains duplicate entries, cannot reshape` if the index/column pair is not unique. In this case, consider using *pivot_table()* which is a generalization of pivot that can handle duplicate values for one index/column pair.

2.8.2 Reshaping by stacking and unstacking



Closely related to the *pivot()* method are the related *stack()* and *unstack()* methods available on `Series` and `DataFrame`. These methods are designed to work together with `MultiIndex` objects (see the section on *hierarchical indexing*). Here are essentially what these methods do:

- `stack`: "pivot" a level of the (possibly hierarchical) column labels, returning a `DataFrame` with an index with a new inner-most level of row labels.
- `unstack`: (inverse operation of `stack`) "pivot" a level of the (possibly hierarchical) row index to the column axis, producing a reshaped `DataFrame` with a new inner-most level of column labels.



The clearest way to explain is by example. Let's take a prior example data set from the hierarchical indexing section:

```
In [8]: tuples = list(
   ...:     zip(
   ...:         *[
   ...:             ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
   ...:             ["one", "two", "one", "two", "one", "two", "one", "two"],
   ...:         ]
   ...:     )
   ...: )
   ...:

In [9]: index = pd.MultiIndex.from_tuples(tuples, names=["first", "second"])

In [10]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=["A", "B"])

In [11]: df2 = df[:4]

In [12]: df2
Out[12]:
                     A         B
first second
bar   one      0.721555 -0.706771
      two     -1.039575  0.271860
baz   one     -0.424972  0.567020
      two      0.276232 -1.087401
```

The `stack` function "compresses" a level in the `DataFrame`'s columns to produce either:

- A `Series`, in the case of a simple column Index.
- A `DataFrame`, in the case of a `MultiIndex` in the columns.

If the columns have a `MultiIndex`, you can choose which level to stack. The stacked level becomes the new lowest

level in a `MultiIndex` on the columns:

```
In [13]: stacked = df2.stack()

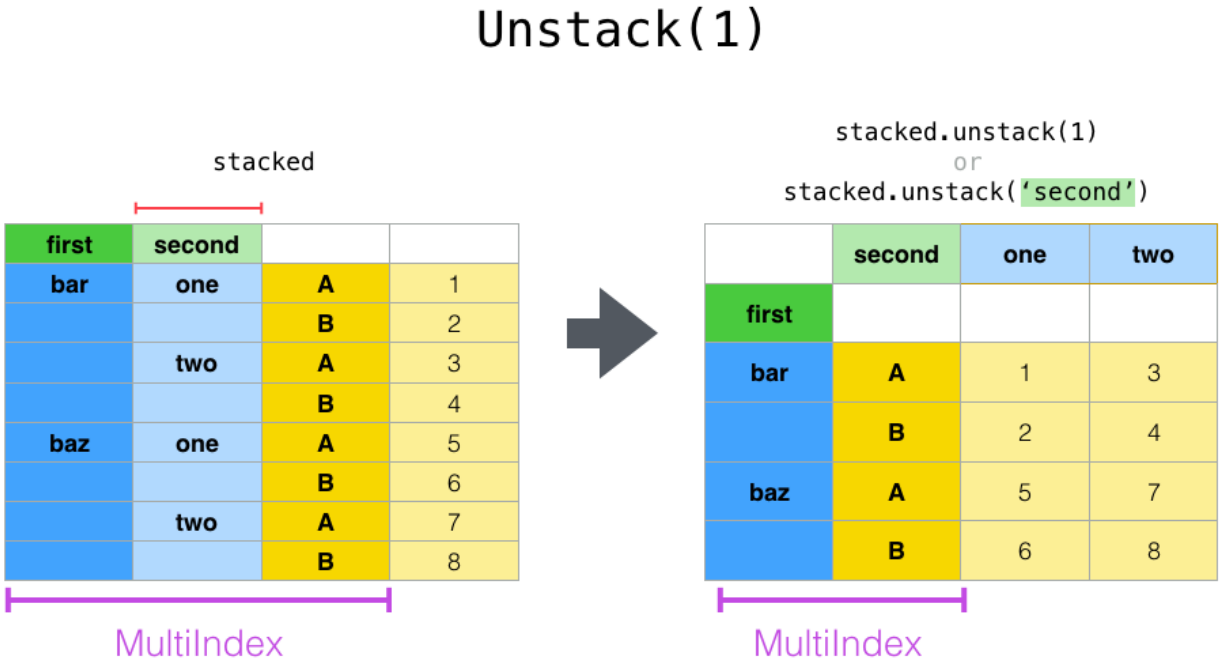
In [14]: stacked
Out[14]:
first  second
bar    one     A    0.721555
                B   -0.706771
       two     A   -1.039575
                B    0.271860
baz    one     A   -0.424972
                B    0.567020
       two     A    0.276232
                B   -1.087401
dtype: float64
```

With a "stacked" `DataFrame` or `Series` (having a `MultiIndex` as the `index`), the inverse operation of `stack` is `unstack`, which by default unstacks the **last level**:

```
In [15]: stacked.unstack()
Out[15]:
                     A         B
first second
bar   one      0.721555 -0.706771
      two     -1.039575  0.271860
baz   one     -0.424972  0.567020
      two      0.276232 -1.087401

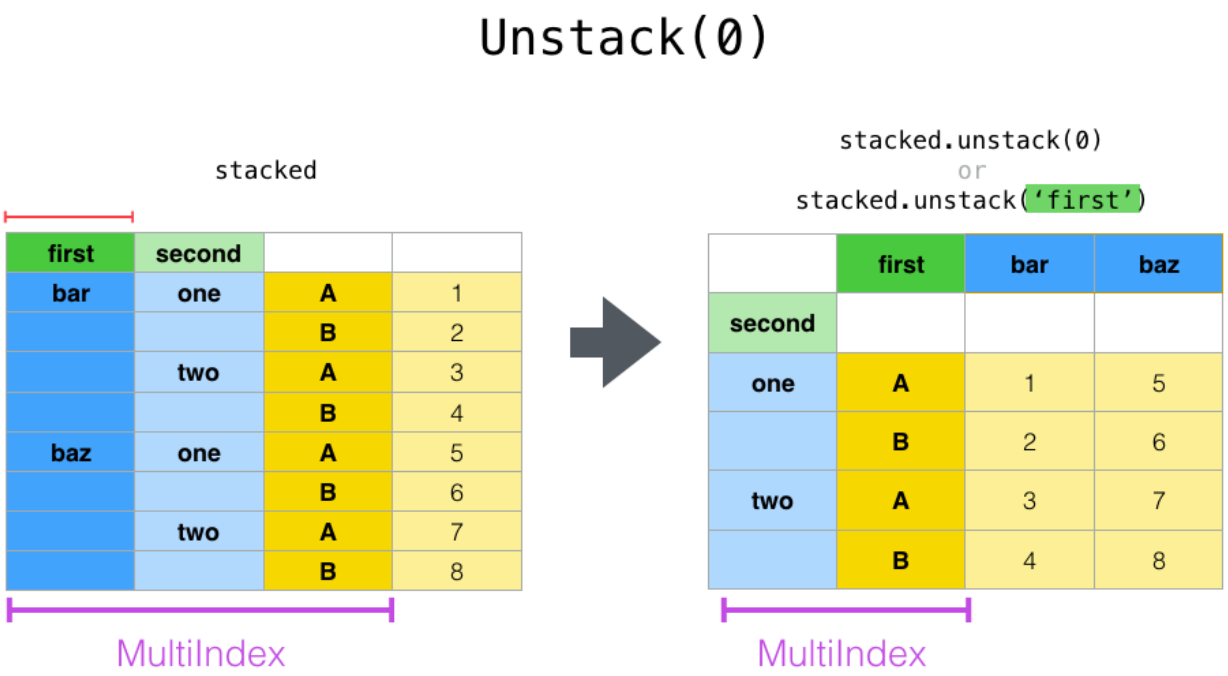
In [16]: stacked.unstack(1)
Out[16]:
second        one       two
first
bar   A  0.721555 -1.039575
      B -0.706771  0.271860
baz   A -0.424972  0.276232
      B  0.567020 -1.087401

In [17]: stacked.unstack(0)
Out[17]:
first          bar       baz
second
one    A  0.721555 -0.424972
       B -0.706771  0.567020
two    A -1.039575  0.276232
       B  0.271860 -1.087401
```



If the indexes have names, you can use the level names instead of specifying the level numbers:

```
In [18]: stacked.unstack("second")
Out[18]:
second        one       two
first
bar   A  0.721555 -1.039575
      B -0.706771  0.271860
baz   A -0.424972  0.276232
      B  0.567020 -1.087401
```



Notice that the `stack` and `unstack` methods implicitly sort the index levels involved. Hence a call to `stack` and then `unstack`, or vice versa, will result in a **sorted** copy of the original `DataFrame` or `Series`:

```
In [19]: index = pd.MultiIndex.from_product([[2, 1], ["a", "b"]])

In [20]: df = pd.DataFrame(np.random.randn(4), index=index, columns=["A"])

In [21]: df
Out[21]:
          A
2 a -0.370647
  b -1.157892
1 a -1.344312
  b  0.844885

In [22]: all(df.unstack().stack() == df.sort_index())
Out[22]: True
```

The above code will raise a `TypeError` if the call to `sort_index` is removed.

Multiple levels

You may also stack or unstack more than one level at a time by passing a list of levels, in which case the end result is as if each level in the list were processed individually.

```
In [23]: columns = pd.MultiIndex.from_tuples(
   ....:     [
   ....:         ("A", "cat", "long"),
   ....:         ("B", "cat", "long"),
   ....:         ("A", "dog", "short"),
   ....:         ("B", "dog", "short"),
   ....:     ],
```

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```
   ....:     names=["exp", "animal", "hair_length"],
   ....: )
   ....:

In [24]: df = pd.DataFrame(np.random.randn(4, 4), columns=columns)

In [25]: df
Out[25]:
exp                A         B         A         B
animal           cat       cat       dog       dog
hair_length     long      long     short     short
0           1.075770 -0.109050  1.643563 -1.469388
1           0.357021 -0.674600 -1.776904 -0.968914
2          -1.294524  0.413738  0.276662 -0.472035
3          -0.013960 -0.362543 -0.006154 -0.923061

In [26]: df.stack(level=["animal", "hair_length"])
Out[26]:
exp                          A         B
  animal hair_length
0 cat    long          1.075770 -0.109050
  dog    short         1.643563 -1.469388
1 cat    long          0.357021 -0.674600
  dog    short        -1.776904 -0.968914
2 cat    long         -1.294524  0.413738
  dog    short         0.276662 -0.472035
3 cat    long         -0.013960 -0.362543
  dog    short        -0.006154 -0.923061
```

The list of levels can contain either level names or level numbers (but not a mixture of the two).

```
# df.stack(level=['animal', 'hair_length'])
# from above is equivalent to:
In [27]: df.stack(level=[1, 2])
Out[27]:
exp                          A         B
  animal hair_length
0 cat    long          1.075770 -0.109050
  dog    short         1.643563 -1.469388
1 cat    long          0.357021 -0.674600
  dog    short        -1.776904 -0.968914
2 cat    long         -1.294524  0.413738
  dog    short         0.276662 -0.472035
3 cat    long         -0.013960 -0.362543
  dog    short        -0.006154 -0.923061
```

Missing data

These functions are intelligent about handling missing data and do not expect each subgroup within the hierarchical index to have the same set of labels. They also can handle the index being unsorted (but you can make it sorted by calling `sort_index`, of course). Here is a more complex example:

```
In [28]: columns = pd.MultiIndex.from_tuples(
   ....:     [
   ....:         ("A", "cat"),
   ....:         ("B", "dog"),
   ....:         ("B", "cat"),
   ....:         ("A", "dog"),
   ....:     ],
   ....:     names=["exp", "animal"],
   ....: )
   ....:

In [29]: index = pd.MultiIndex.from_product(
   ....:     [("bar", "baz", "foo", "qux"), ("one", "two")], names=["first", "second"]
   ....: )
   ....:

In [30]: df = pd.DataFrame(np.random.randn(8, 4), index=index, columns=columns)

In [31]: df2 = df.iloc[[0, 1, 2, 4, 5, 7]]

In [32]: df2
Out[32]:
exp                   A         B                   A
animal              cat       dog       cat       dog
first second
bar   one     0.895717  0.805244 -1.206412  2.565646
      two     1.431256  1.340309 -1.170299 -0.226169
baz   one     0.410835  0.813850  0.132003 -0.827317
foo   one    -1.413681  1.607920  1.024180  0.569605
      two     0.875906 -2.211372  0.974466 -2.006747
qux   two    -1.226825  0.769804 -1.281247 -0.727707
```

As mentioned above, `stack` can be called with a `level` argument to select which level in the columns to stack:

```
In [33]: df2.stack("exp")
Out[33]:
animal                 cat       dog
first second exp
bar   one    A     0.895717  2.565646
             B    -1.206412  0.805244
      two    A     1.431256 -0.226169
             B    -1.170299  1.340309
baz   one    A     0.410835 -0.827317
             B     0.132003  0.813850
foo   one    A    -1.413681  0.569605
             B     1.024180  1.607920
      two    A     0.875906 -2.006747
             B     0.974466 -2.211372
qux   two    A    -1.226825 -0.727707
             B    -1.281247  0.769804

In [34]: df2.stack("animal")
```

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```
Out[34]:
exp                          A         B
first second animal
bar   one    cat      0.895717 -1.206412
             dog      2.565646  0.805244
      two    cat      1.431256 -1.170299
             dog     -0.226169  1.340309
baz   one    cat      0.410835  0.132003
             dog     -0.827317  0.813850
foo   one    cat     -1.413681  1.024180
             dog      0.569605  1.607920
      two    cat      0.875906  0.974466
             dog     -2.006747 -2.211372
qux   two    cat     -1.226825 -1.281247
             dog     -0.727707  0.769804
```

Unstacking can result in missing values if subgroups do not have the same set of labels. By default, missing values will be replaced with the default fill value for that data type, `NaN` for float, `NaT` for datetimelike, etc. For integer types, by default data will converted to float and missing values will be set to `NaN`.

```
In [35]: df3 = df.iloc[[0, 1, 4, 7], [1, 2]]

In [36]: df3
Out[36]:
exp                   B
animal              dog       cat
first second
bar   one      0.805244 -1.206412
      two      1.340309 -1.170299
foo   one      1.607920  1.024180
qux   two      0.769804 -1.281247

In [37]: df3.unstack()
Out[37]:
exp            B
animal       dog                 cat
second       one       two       one       two
first
bar     0.805244  1.340309 -1.206412 -1.170299
foo     1.607920       NaN  1.024180       NaN
qux          NaN  0.769804       NaN -1.281247
```

Alternatively, unstack takes an optional `fill_value` argument, for specifying the value of missing data.

```
In [38]: df3.unstack(fill_value=-1e9)
Out[38]:
exp                B
animal           dog                          cat
second           one           two           one           two
first
bar     8.052440e-01  1.340309e+00 -1.206412e+00 -1.170299e+00
foo     1.607920e+00 -1.000000e+09  1.024180e+00 -1.000000e+09
qux    -1.000000e+09  7.698036e-01 -1.000000e+09 -1.281247e+00
```

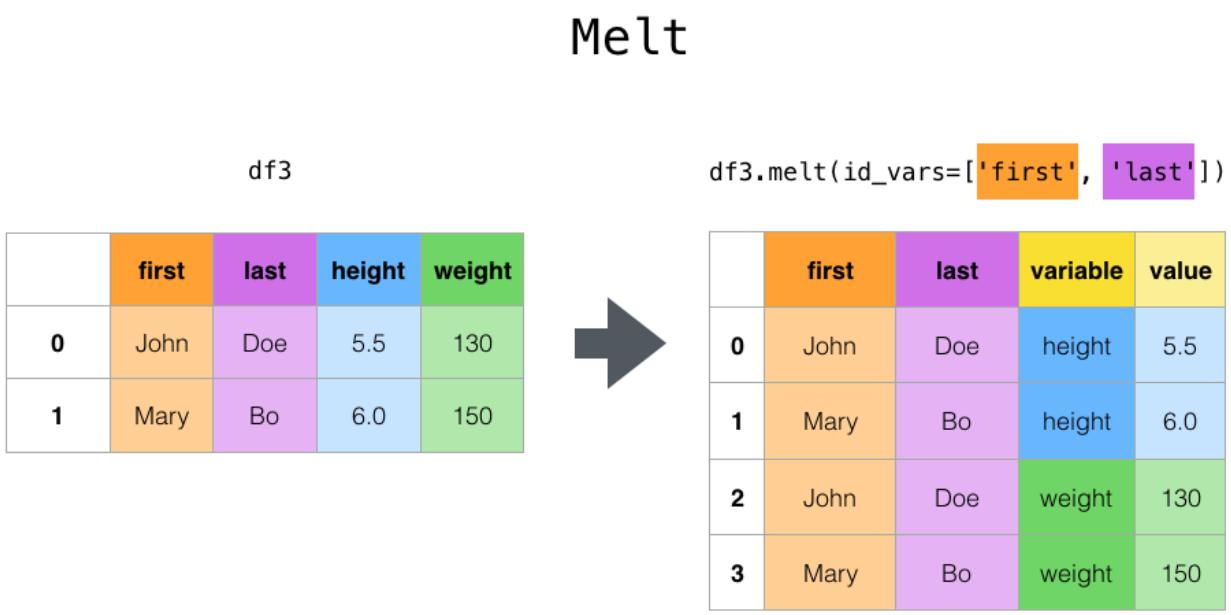
With a MultiIndex

Unstacking when the columns are a `MultiIndex` is also careful about doing the right thing:

```
In [39]: df[:3].unstack(0)
Out[39]:
exp            A                   B                                   A
animal       cat                 dog                 cat                 dog
first        bar       baz       bar       baz       bar       baz       bar       baz
second
one     0.895717  0.410835  0.805244  0.81385 -1.206412  0.132003  2.565646 -0.827317
two     1.431256       NaN  1.340309      NaN -1.170299       NaN -0.226169       NaN

In [40]: df2.unstack(1)
Out[40]:
exp            A                   B                                   A
animal       cat                 dog                 cat                 dog
second       one       two       one       two       one       two       one       two
first
bar     0.895717  1.431256  0.805244  1.340309 -1.206412 -1.170299  2.565646 -0.226169
baz     0.410835       NaN  0.813850       NaN  0.132003       NaN -0.827317       NaN
foo    -1.413681  0.875906  1.607920 -2.211372  1.024180  0.974466  0.569605 -2.006747
qux          NaN -1.226825       NaN  0.769804       NaN -1.281247       NaN -0.727707
```

2.8.3 Reshaping by melt



The top-level *melt()* function and the corresponding *DataFrame.melt()* are useful to massage a `DataFrame` into a format where one or more columns are *identifier variables*, while all other columns, considered *measured variables*, are "unpivoted" to the row axis, leaving just two non-identifier columns, "variable" and "value". The names of those columns can be customized by supplying the `var_name` and `value_name` parameters.

For instance,

```
In [41]: cheese = pd.DataFrame(
   ....:     {
   ....:         "first": ["John", "Mary"],
   ....:         "last": ["Doe", "Bo"],
   ....:         "height": [5.5, 6.0],
   ....:         "weight": [130, 150],
   ....:     }
   ....: )
   ....:

In [42]: cheese
Out[42]:
  first last  height  weight
0  John  Doe     5.5     130
1  Mary   Bo     6.0     150

In [43]: cheese.melt(id_vars=["first", "last"])
Out[43]:
  first last variable  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0

In [44]: cheese.melt(id_vars=["first", "last"], var_name="quantity")
Out[44]:
  first last quantity  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0
```

When transforming a DataFrame using *melt()*, the index will be ignored. The original index values can be kept around by setting the `ignore_index` parameter to `False` (default is `True`). This will however duplicate them.

New in version 1.1.0.

```
In [45]: index = pd.MultiIndex.from_tuples([("person", "A"), ("person", "B")])

In [46]: cheese = pd.DataFrame(
   ....:     {
   ....:         "first": ["John", "Mary"],
   ....:         "last": ["Doe", "Bo"],
   ....:         "height": [5.5, 6.0],
   ....:         "weight": [130, 150],
   ....:     },
   ....:     index=index,
   ....: )
   ....:

In [47]: cheese
Out[47]:
         first last  height  weight
person A  John  Doe     5.5     130
       B  Mary   Bo     6.0     150

In [48]: cheese.melt(id_vars=["first", "last"])
Out[48]:
```

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```
  first last variable  value
0  John  Doe   height    5.5
1  Mary   Bo   height    6.0
2  John  Doe   weight  130.0
3  Mary   Bo   weight  150.0

In [49]: cheese.melt(id_vars=["first", "last"], ignore_index=False)
Out[49]:
         first last variable  value
person A  John  Doe   height    5.5
       B  Mary   Bo   height    6.0
       A  John  Doe   weight  130.0
       B  Mary   Bo   weight  150.0
```

Another way to transform is to use the *wide_to_long()* panel data convenience function. It is less flexible than *melt()*, but more user-friendly.

```
In [50]: dft = pd.DataFrame(
   ....:     {
   ....:         "A1970": {0: "a", 1: "b", 2: "c"},
   ....:         "A1980": {0: "d", 1: "e", 2: "f"},
   ....:         "B1970": {0: 2.5, 1: 1.2, 2: 0.7},
   ....:         "B1980": {0: 3.2, 1: 1.3, 2: 0.1},
   ....:         "X": dict(zip(range(3), np.random.randn(3))),
   ....:     }
   ....: )
   ....:

In [51]: dft["id"] = dft.index

In [52]: dft
Out[52]:
  A1970 A1980  B1970  B1980         X  id
0     a     d    2.5    3.2 -0.121306   0
1     b     e    1.2    1.3 -0.097883   1
2     c     f    0.7    0.1  0.695775   2

In [53]: pd.wide_to_long(dft, ["A", "B"], i="id", j="year")
Out[53]:
                X  A    B
id year
0  1970 -0.121306  a  2.5
1  1970 -0.097883  b  1.2
2  1970  0.695775  c  0.7
0  1980 -0.121306  d  3.2
1  1980 -0.097883  e  1.3
2  1980  0.695775  f  0.1
```

2.8.4 Combining with stats and GroupBy

It should be no shock that combining `pivot` / `stack` / `unstack` with GroupBy and the basic Series and DataFrame statistical functions can produce some very expressive and fast data manipulations.

```
In [54]: df
Out[54]:
exp                  A         B                   A
animal             cat       dog       cat       dog
first second
bar   one     0.895717  0.805244 -1.206412  2.565646
      two     1.431256  1.340309 -1.170299 -0.226169
baz   one     0.410835  0.813850  0.132003 -0.827317
      two    -0.076467 -1.187678  1.130127 -1.436737
foo   one    -1.413681  1.607920  1.024180  0.569605
      two     0.875906 -2.211372  0.974466 -2.006747
qux   one    -0.410001 -0.078638  0.545952 -1.219217
      two    -1.226825  0.769804 -1.281247 -0.727707

In [55]: df.stack().mean(1).unstack()
Out[55]:
animal             cat       dog
first second
bar   one    -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one    -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two    -1.254036  0.021048

# same result, another way
In [56]: df.groupby(level=1, axis=1).mean()
Out[56]:
animal             cat       dog
first second
bar   one    -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one    -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two    -1.254036  0.021048

In [57]: df.stack().groupby(level=1).mean()
Out[57]:
exp            A         B
second
one     0.071448  0.455513
two    -0.424186 -0.204486

In [58]: df.mean().unstack(0)
Out[58]:
exp            A         B
animal
cat     0.060843  0.018596
```

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```
dog    -0.413580  0.232430
```

2.8.5 Pivot tables

While *pivot()* provides general purpose pivoting with various data types (strings, numerics, etc.), pandas also provides *pivot_table()* for pivoting with aggregation of numeric data.

The function *pivot_table()* can be used to create spreadsheet-style pivot tables. See the *cookbook* for some advanced strategies.

It takes a number of arguments:

- `data`: a DataFrame object.
- `values`: a column or a list of columns to aggregate.
- `index`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.
- `columns`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.
- `aggfunc`: function to use for aggregation, defaulting to `numpy.mean`.

Consider a data set like this:

```
In [59]: import datetime

In [60]: df = pd.DataFrame(
   ....:     {
   ....:         "A": ["one", "one", "two", "three"] * 6,
   ....:         "B": ["A", "B", "C"] * 8,
   ....:         "C": ["foo", "foo", "foo", "bar", "bar", "bar"] * 4,
   ....:         "D": np.random.randn(24),
   ....:         "E": np.random.randn(24),
   ....:         "F": [datetime.datetime(2013, i, 1) for i in range(1, 13)]
   ....:         + [datetime.datetime(2013, i, 15) for i in range(1, 13)],
   ....:     }
   ....: )
   ....:

In [61]: df
Out[61]:
        A  B    C         D         E          F
0     one  A  foo  0.341734 -0.317441 2013-01-01
1     one  B  foo  0.959726 -1.236269 2013-02-01
2     two  C  foo -1.110336  0.896171 2013-03-01
3   three  A  bar -0.619976 -0.487602 2013-04-01
4     one  B  bar  0.149748 -0.082240 2013-05-01
..    ... ..  ...       ...       ...        ...
19  three  B  foo  0.690579 -2.213588 2013-08-15
20    one  C  foo  0.995761  1.063327 2013-09-15
21    one  A  bar  2.396780  1.266143 2013-10-15
22    two  B  bar  0.014871  0.299368 2013-11-15
23  three  C  bar  3.357427 -0.863838 2013-12-15

[24 rows x 6 columns]
```

We can produce pivot tables from this data very easily:

```
In [62]: pd.pivot_table(df, values="D", index=["A", "B"], columns=["C"])
Out[62]:
C             bar       foo
A     B
one   A  1.120915 -0.514058
      B -0.338421  0.002759
      C -0.538846  0.699535
three A -1.181568       NaN
      B       NaN  0.433512
      C  0.588783       NaN
two   A       NaN  1.000985
      B  0.158248       NaN
      C       NaN  0.176180

In [63]: pd.pivot_table(df, values="D", index=["B"], columns=["A", "C"], aggfunc=np.
↪sum)
Out[63]:
A       one               three                 two
C       bar       foo       bar       foo       bar       foo
B
A  2.241830 -1.028115 -2.363137       NaN       NaN  2.001971
B -0.676843  0.005518       NaN  0.867024  0.316495       NaN
C -1.077692  1.399070  1.177566       NaN       NaN  0.352360

In [64]: pd.pivot_table(
   ....:     df, values=["D", "E"],
   ....:     index=["B"],
   ....:     columns=["A", "C"],
   ....:     aggfunc=np.sum,
   ....: )
   ....:
Out[64]:
          D                                                                E                ␣
↪
A       one               three                 two                 one                ␣
↪three                 two
C       bar       foo       bar       foo       bar       foo       bar       foo      ␣
↪  bar       foo       bar       foo
B                                                                                        ␣
↪
A  2.241830 -1.028115 -2.363137       NaN       NaN  2.001971  2.786113 -0.043211  1.
↪922577       NaN       NaN  0.128491
B -0.676843  0.005518       NaN  0.867024  0.316495       NaN  1.368280 -1.103384      ␣
↪  NaN -2.128743 -0.194294       NaN
C -1.077692  1.399070  1.177566       NaN       NaN  0.352360 -1.976883  1.495717 -0.
↪263660       NaN       NaN  0.872482
```

The result object is a `DataFrame` having potentially hierarchical indexes on the rows and columns. If the `values` column name is not given, the pivot table will include all of the data that can be aggregated in an additional level of hierarchy in the columns:

```
In [65]: pd.pivot_table(df, index=["A", "B"], columns=["C"])
Out[65]:
                D                   E
C             bar       foo       bar       foo
A     B
```

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```
one   A  1.120915 -0.514058  1.393057 -0.021605
      B -0.338421  0.002759  0.684140 -0.551692
      C -0.538846  0.699535 -0.988442  0.747859
three A -1.181568       NaN  0.961289       NaN
      B       NaN  0.433512       NaN -1.064372
      C  0.588783       NaN -0.131830       NaN
two   A       NaN  1.000985       NaN  0.064245
      B  0.158248       NaN -0.097147       NaN
      C       NaN  0.176180       NaN  0.436241
```

Also, you can use `Grouper` for `index` and `columns` keywords. For detail of `Grouper`, see *Grouping with a Grouper specification*.

```
In [66]: pd.pivot_table(df, values="D", index=pd.Grouper(freq="M", key="F"), columns=
↪"C")
Out[66]:
C                bar       foo
F
2013-01-31       NaN -0.514058
2013-02-28       NaN  0.002759
2013-03-31       NaN  0.176180
2013-04-30 -1.181568       NaN
2013-05-31 -0.338421       NaN
2013-06-30 -0.538846       NaN
2013-07-31       NaN  1.000985
2013-08-31       NaN  0.433512
2013-09-30       NaN  0.699535
2013-10-31  1.120915       NaN
2013-11-30  0.158248       NaN
2013-12-31  0.588783       NaN
```

You can render a nice output of the table omitting the missing values by calling `to_string` if you wish:

```
In [67]: table = pd.pivot_table(df, index=["A", "B"], columns=["C"])

In [68]: print(table.to_string(na_rep=""))
                D                   E
C             bar       foo       bar       foo
A     B
one   A  1.120915 -0.514058  1.393057 -0.021605
      B -0.338421  0.002759  0.684140 -0.551692
      C -0.538846  0.699535 -0.988442  0.747859
three A -1.181568            0.961289
      B            0.433512           -1.064372
      C  0.588783           -0.131830
two   A            1.000985            0.064245
      B  0.158248           -0.097147
      C            0.176180            0.436241
```

Note that `pivot_table` is also available as an instance method on DataFrame, i.e. *`DataFrame.pivot_table()`*.

Adding margins

If you pass `margins=True` to `pivot_table`, special `All` columns and rows will be added with partial group aggregates across the categories on the rows and columns:

```
In [69]: df.pivot_table(index=["A", "B"], columns="C", margins=True, aggfunc=np.std)
Out[69]:
                D                             E
C             bar       foo       All       bar       foo       All
A     B
one   A  1.804346  1.210272  1.569879  0.179483  0.418374  0.858005
      B  0.690376  1.353355  0.898998  1.083825  0.968138  1.101401
      C  0.273641  0.418926  0.771139  1.689271  0.446140  1.422136
three A  0.794212       NaN  0.794212  2.049040       NaN  2.049040
      B       NaN  0.363548  0.363548       NaN  1.625237  1.625237
      C  3.915454       NaN  3.915454  1.035215       NaN  1.035215
two   A       NaN  0.442998  0.442998       NaN  0.447104  0.447104
      B  0.202765       NaN  0.202765  0.560757       NaN  0.560757
      C       NaN  1.819408  1.819408       NaN  0.650439  0.650439
All      1.556686  0.952552  1.246608  1.250924  0.899904  1.059389
```

2.8.6 Cross tabulations

Use *crosstab()* to compute a cross-tabulation of two (or more) factors. By default `crosstab` computes a frequency table of the factors unless an array of values and an aggregation function are passed.

It takes a number of arguments

- `index`: array-like, values to group by in the rows.
- `columns`: array-like, values to group by in the columns.
- `values`: array-like, optional, array of values to aggregate according to the factors.
- `aggfunc`: function, optional, If no values array is passed, computes a frequency table.
- `rownames`: sequence, default `None`, must match number of row arrays passed.
- `colnames`: sequence, default `None`, if passed, must match number of column arrays passed.
- `margins`: boolean, default `False`, Add row/column margins (subtotals)
- `normalize`: boolean, {'all', 'index', 'columns'}, or {0,1}, default `False`. Normalize by dividing all values by the sum of values.

Any `Series` passed will have their name attributes used unless row or column names for the cross-tabulation are specified

For example:

```
In [70]: foo, bar, dull, shiny, one, two = "foo", "bar", "dull", "shiny", "one", "two"

In [71]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)

In [72]: b = np.array([one, one, two, one, two, one], dtype=object)

In [73]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)

In [74]: pd.crosstab(a, [b, c], rownames=["a"], colnames=["b", "c"])
Out[74]:
```

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```
b    one        two
c   dull shiny dull shiny
a
bar    1     0    0     1
foo    2     1    1     0
```

If `crosstab` receives only two Series, it will provide a frequency table.

```
In [75]: df = pd.DataFrame(
   ....:     {"A": [1, 2, 2, 2, 2], "B": [3, 3, 4, 4, 4], "C": [1, 1, np.nan, 1, 1]}
   ....: )
   ....:

In [76]: df
Out[76]:
   A  B    C
0  1  3  1.0
1  2  3  1.0
2  2  4  NaN
3  2  4  1.0
4  2  4  1.0

In [77]: pd.crosstab(df["A"], df["B"])
Out[77]:
B  3  4
A
1  1  0
2  1  3
```

`crosstab` can also be implemented to `Categorical` data.

```
In [78]: foo = pd.Categorical(["a", "b"], categories=["a", "b", "c"])

In [79]: bar = pd.Categorical(["d", "e"], categories=["d", "e", "f"])

In [80]: pd.crosstab(foo, bar)
Out[80]:
col_0  d  e
row_0
a      1  0
b      0  1
```

If you want to include **all** of data categories even if the actual data does not contain any instances of a particular category, you should set `dropna=False`.

For example:

```
In [81]: pd.crosstab(foo, bar, dropna=False)
Out[81]:
col_0  d  e  f
row_0
a      1  0  0
b      0  1  0
c      0  0  0
```

Normalization

Frequency tables can also be normalized to show percentages rather than counts using the `normalize` argument:

```
In [82]: pd.crosstab(df["A"], df["B"], normalize=True)
Out[82]:
B    3    4
A
1  0.2  0.0
2  0.2  0.6
```

`normalize` can also normalize values within each row or within each column:

```
In [83]: pd.crosstab(df["A"], df["B"], normalize="columns")
Out[83]:
B    3    4
A
1  0.5  0.0
2  0.5  1.0
```

`crosstab` can also be passed a third `Series` and an aggregation function (`aggfunc`) that will be applied to the values of the third `Series` within each group defined by the first two `Series`:

```
In [84]: pd.crosstab(df["A"], df["B"], values=df["C"], aggfunc=np.sum)
Out[84]:
B    3    4
A
1  1.0  NaN
2  1.0  2.0
```

Adding margins

Finally, one can also add margins or normalize this output.

```
In [85]: pd.crosstab(
   ....:     df["A"], df["B"], values=df["C"], aggfunc=np.sum, normalize=True,␣
↪margins=True
   ....: )
   ....:
Out[85]:
B       3    4   All
A
1    0.25  0.0  0.25
2    0.25  0.5  0.75
All  0.50  0.5  1.00
```

2.8.7 Tiling

The *cut()* function computes groupings for the values of the input array and is often used to transform continuous variables to discrete or categorical variables:

```
In [86]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])

In [87]: pd.cut(ages, bins=3)
Out[87]:
[(9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.
↪95, 26.667], (26.667, 43.333], (43.333, 60.0], (43.333, 60.0]]
Categories (3, interval[float64]): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60.
↪0]]
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```
In [88]: c = pd.cut(ages, bins=[0, 18, 35, 70])

In [89]: c
Out[89]:
[(0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35], (35, 70], (35, 70]]
Categories (3, interval[int64]): [(0, 18] < (18, 35] < (35, 70]]
```

If the `bins` keyword is an `IntervalIndex`, then these will be used to bin the passed data.:

```
pd.cut([25, 20, 50], bins=c.categories)
```

2.8.8 Computing indicator / dummy variables

To convert a categorical variable into a "dummy" or "indicator" `DataFrame`, for example a column in a `DataFrame` (a `Series`) which has `k` distinct values, can derive a `DataFrame` containing `k` columns of 1s and 0s using *get_dummies()*:

```
In [90]: df = pd.DataFrame({"key": list("bbacab"), "data1": range(6)})

In [91]: pd.get_dummies(df["key"])
Out[91]:
   a  b  c
0  0  1  0
1  0  1  0
2  1  0  0
3  0  0  1
4  1  0  0
5  0  1  0
```

Sometimes it's useful to prefix the column names, for example when merging the result with the original `DataFrame`:

```
In [92]: dummies = pd.get_dummies(df["key"], prefix="key")

In [93]: dummies
Out[93]:
   key_a  key_b  key_c
0      0      1      0
1      0      1      0
2      1      0      0
3      0      0      1
```

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```
4       1       0       0
5       0       1       0

In [94]: df[["data1"]].join(dummies)
Out[94]:
   data1  key_a  key_b  key_c
0      0      0      1      0
1      1      0      1      0
2      2      1      0      0
3      3      0      0      1
4      4      1      0      0
5      5      0      1      0
```

This function is often used along with discretization functions like `cut`:

```
In [95]: values = np.random.randn(10)

In [96]: values
Out[96]:
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29  ,
        0.0824, -0.0558,  0.5366])

In [97]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]

In [98]: pd.get_dummies(pd.cut(values, bins))
Out[98]:
   (0.0, 0.2]  (0.2, 0.4]  (0.4, 0.6]  (0.6, 0.8]  (0.8, 1.0]
0           0           0           1           0           0
1           0           0           0           0           0
2           0           0           0           0           0
3           0           0           0           0           0
4           1           0           0           0           0
5           0           0           0           0           0
6           0           0           0           0           0
7           1           0           0           0           0
8           0           0           0           0           0
9           0           0           1           0           0
```

See also *`Series.str.get_dummies`*.

`get_dummies()` also accepts a `DataFrame`. By default all categorical variables (categorical in the statistical sense, those with `object` or `categorical` dtype) are encoded as dummy variables.

```
In [99]: df = pd.DataFrame({"A": ["a", "b", "a"], "B": ["c", "c", "b"], "C": [1, 2,␣
↪3]})

In [100]: pd.get_dummies(df)
Out[100]:
   C  A_a  A_b  B_b  B_c
0  1    1    0    0    1
1  2    0    1    0    1
2  3    1    0    1    0
```

All non-object columns are included untouched in the output. You can control the columns that are encoded with the `columns` keyword.

```
In [101]: pd.get_dummies(df, columns=["A"])
Out[101]:
   B  C  A_a  A_b
0  c  1    1    0
1  c  2    0    1
2  b  3    1    0
```

Notice that the `B` column is still included in the output, it just hasn't been encoded. You can drop `B` before calling `get_dummies` if you don't want to include it in the output.

As with the `Series` version, you can pass values for the `prefix` and `prefix_sep`. By default the column name is used as the prefix, and '_' as the prefix separator. You can specify `prefix` and `prefix_sep` in 3 ways:

- string: Use the same value for `prefix` or `prefix_sep` for each column to be encoded.
- list: Must be the same length as the number of columns being encoded.
- dict: Mapping column name to prefix.

```
In [102]: simple = pd.get_dummies(df, prefix="new_prefix")

In [103]: simple
Out[103]:
   C  new_prefix_a  new_prefix_b  new_prefix_b  new_prefix_c
0  1             1             0             0             1
1  2             0             1             0             1
2  3             1             0             1             0

In [104]: from_list = pd.get_dummies(df, prefix=["from_A", "from_B"])

In [105]: from_list
Out[105]:
   C  from_A_a  from_A_b  from_B_b  from_B_c
0  1         1         0         0         1
1  2         0         1         0         1
2  3         1         0         1         0

In [106]: from_dict = pd.get_dummies(df, prefix={"B": "from_B", "A": "from_A"})

In [107]: from_dict
Out[107]:
   C  from_A_a  from_A_b  from_B_b  from_B_c
0  1         1         0         0         1
1  2         0         1         0         1
2  3         1         0         1         0
```

Sometimes it will be useful to only keep k-1 levels of a categorical variable to avoid collinearity when feeding the result to statistical models. You can switch to this mode by turn on `drop_first`.

```
In [108]: s = pd.Series(list("abcaa"))

In [109]: pd.get_dummies(s)
Out[109]:
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0
```

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```
4  1  0  0

In [110]: pd.get_dummies(s, drop_first=True)
Out[110]:
   b  c
0  0  0
1  1  0
2  0  1
3  0  0
4  0  0
```

When a column contains only one level, it will be omitted in the result.

```
In [111]: df = pd.DataFrame({"A": list("aaaaa"), "B": list("ababc")})

In [112]: pd.get_dummies(df)
Out[112]:
   A_a  B_a  B_b  B_c
0    1    1    0    0
1    1    0    1    0
2    1    1    0    0
3    1    0    1    0
4    1    0    0    1

In [113]: pd.get_dummies(df, drop_first=True)
Out[113]:
   B_b  B_c
0    0    0
1    1    0
2    0    0
3    1    0
4    0    1
```

By default new columns will have `np.uint8` dtype. To choose another dtype, use the `dtype` argument:

```
In [114]: df = pd.DataFrame({"A": list("abc"), "B": [1.1, 2.2, 3.3]})

In [115]: pd.get_dummies(df, dtype=bool).dtypes
Out[115]:
B      float64
A_a       bool
A_b       bool
A_c       bool
dtype: object
```

2.8.9 Factorizing values

To encode 1-d values as an enumerated type use *`factorize()`*:

```
In [116]: x = pd.Series(["A", "A", np.nan, "B", 3.14, np.inf])

In [117]: x
Out[117]:
0       A
1       A
```

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```
2     NaN
3       B
4    3.14
5     inf
dtype: object

In [118]: labels, uniques = pd.factorize(x)

In [119]: labels
Out[119]: array([ 0,  0, -1,  1,  2,  3])

In [120]: uniques
Out[120]: Index(['A', 'B', 3.14, inf], dtype='object')
```

Note that `factorize` is similar to `numpy.unique`, but differs in its handling of NaN:

Note: The following `numpy.unique` will fail under Python 3 with a `TypeError` because of an ordering bug. See also here.

```
In [1]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])
In [2]: pd.factorize(x, sort=True)
Out[2]:
(array([ 2,  2, -1,  3,  0,  1]),
 Index([3.14, inf, 'A', 'B'], dtype='object'))

In [3]: np.unique(x, return_inverse=True)[::-1]
Out[3]: (array([3, 3, 0, 4, 1, 2]), array([nan, 3.14, inf, 'A', 'B'], dtype=object))
```

Note: If you just want to handle one column as a categorical variable (like R's factor), you can use `df["cat_col"] = pd.Categorical(df["col"])` or `df["cat_col"] = df["col"].astype("category")`. For full docs on *`Categorical`*, see the *Categorical introduction* and the *API documentation*.

2.8.10 Examples

In this section, we will review frequently asked questions and examples. The column names and relevant column values are named to correspond with how this DataFrame will be pivoted in the answers below.

```
In [121]: np.random.seed([3, 1415])

In [122]: n = 20

In [123]: cols = np.array(["key", "row", "item", "col"])

In [124]: df = cols + pd.DataFrame(
   .....:     (np.random.randint(5, size=(n, 4)) // [2, 1, 2, 1]).astype(str)
   .....: )
   .....:

In [125]: df.columns = cols

In [126]: df = df.join(pd.DataFrame(np.random.rand(n, 2).round(2)).add_prefix("val"))
```

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```
In [127]: df
Out[127]:
     key   row   item   col  val0  val1
0   key0  row3  item1  col3  0.81  0.04
1   key1  row2  item1  col2  0.44  0.07
2   key1  row0  item1  col0  0.77  0.01
3   key0  row4  item0  col2  0.15  0.59
4   key1  row0  item2  col1  0.81  0.64
..   ...   ...    ...   ...   ...   ...
15  key0  row3  item1  col1  0.31  0.23
16  key0  row0  item2  col3  0.86  0.01
17  key0  row4  item0  col3  0.64  0.21
18  key2  row2  item2  col0  0.13  0.45
19  key0  row2  item0  col4  0.37  0.70

[20 rows x 6 columns]
```

Pivoting with single aggregations

Suppose we wanted to pivot `df` such that the `col` values are columns, `row` values are the index, and the mean of `val0` are the values? In particular, the resulting DataFrame should look like:

```
col   col0   col1   col2   col3  col4
row
row0  0.77  0.605    NaN  0.860  0.65
row2  0.13    NaN  0.395  0.500  0.25
row3   NaN  0.310    NaN  0.545   NaN
row4   NaN  0.100  0.395  0.760  0.24
```

This solution uses *`pivot_table()`*. Also note that `aggfunc='mean'` is the default. It is included here to be explicit.

```
In [128]: df.pivot_table(values="val0", index="row", columns="col", aggfunc="mean")
Out[128]:
col   col0   col1   col2   col3  col4
row
row0  0.77  0.605    NaN  0.860  0.65
row2  0.13    NaN  0.395  0.500  0.25
row3   NaN  0.310    NaN  0.545   NaN
row4   NaN  0.100  0.395  0.760  0.24
```

Note that we can also replace the missing values by using the `fill_value` parameter.

```
In [129]: df.pivot_table(
   .....:     values="val0",
   .....:     index="row",
   .....:     columns="col",
   .....:     aggfunc="mean",
   .....:     fill_value=0,
   .....: )
   .....:
Out[129]:
col   col0   col1   col2   col3  col4
row
```

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```
row0  0.77  0.605  0.000  0.860  0.65
row2  0.13  0.000  0.395  0.500  0.25
row3  0.00  0.310  0.000  0.545  0.00
row4  0.00  0.100  0.395  0.760  0.24
```

Also note that we can pass in other aggregation functions as well. For example, we can also pass in `sum`.

```
In [130]: df.pivot_table(
   .....:     values="val0",
   .....:     index="row",
   .....:     columns="col",
   .....:     aggfunc="sum",
   .....:     fill_value=0,
   .....: )
   .....:
Out[130]:
col   col0  col1  col2  col3  col4
row
row0  0.77  1.21  0.00  0.86  0.65
row2  0.13  0.00  0.79  0.50  0.50
row3  0.00  0.31  0.00  1.09  0.00
row4  0.00  0.10  0.79  1.52  0.24
```

Another aggregation we can do is calculate the frequency in which the columns and rows occur together a.k.a. "cross tabulation". To do this, we can pass `size` to the `aggfunc` parameter.

```
In [131]: df.pivot_table(index="row", columns="col", fill_value=0, aggfunc="size")
Out[131]:
col   col0  col1  col2  col3  col4
row
row0     1     2     0     1     1
row2     1     0     2     1     2
row3     0     1     0     2     0
row4     0     1     2     2     1
```

Pivoting with multiple aggregations

We can also perform multiple aggregations. For example, to perform both a `sum` and `mean`, we can pass in a list to the `aggfunc` argument.

```
In [132]: df.pivot_table(
   .....:     values="val0",
   .....:     index="row",
   .....:     columns="col",
   .....:     aggfunc=["mean", "sum"],
   .....: )
   .....:
Out[132]:
      mean                                sum
col   col0   col1   col2   col3  col4  col0  col1  col2  col3  col4
row
row0  0.77  0.605    NaN  0.860  0.65  0.77  1.21   NaN  0.86  0.65
row2  0.13    NaN  0.395  0.500  0.25  0.13   NaN  0.79  0.50  0.50
row3   NaN  0.310    NaN  0.545   NaN   NaN  0.31   NaN  1.09   NaN
row4   NaN  0.100  0.395  0.760  0.24   NaN  0.10  0.79  1.52  0.24
```

Note to aggregate over multiple value columns, we can pass in a list to the `values` parameter.

```
In [133]: df.pivot_table(
   .....:     values=["val0", "val1"],
   .....:     index="row",
   .....:     columns="col",
   .....:     aggfunc=["mean"],
   .....: )
   .....:
Out[133]:
      mean
      val0                              val1
col   col0   col1   col2   col3  col4  col0   col1  col2   col3  col4
row
row0  0.77  0.605    NaN  0.860  0.65  0.01  0.745   NaN  0.010  0.02
row2  0.13    NaN  0.395  0.500  0.25  0.45    NaN  0.34  0.440  0.79
row3   NaN  0.310    NaN  0.545   NaN   NaN  0.230   NaN  0.075   NaN
row4   NaN  0.100  0.395  0.760  0.24   NaN  0.070  0.42  0.300  0.46
```

Note to subdivide over multiple columns we can pass in a list to the `columns` parameter.

```
In [134]: df.pivot_table(
   .....:     values=["val0"],
   .....:     index="row",
   .....:     columns=["item", "col"],
   .....:     aggfunc=["mean"],
   .....: )
   .....:
Out[134]:
      mean
      val0
item item0             item1                          item2
col   col2  col3  col4  col0  col1  col2  col3  col4  col0   col1  col3  col4
row
row0   NaN   NaN   NaN  0.77   NaN   NaN   NaN   NaN   NaN  0.605  0.86  0.65
row2  0.35   NaN  0.37   NaN   NaN  0.44   NaN   NaN  0.13    NaN  0.50  0.13
row3   NaN   NaN   NaN   NaN  0.31   NaN  0.81   NaN   NaN    NaN  0.28   NaN
row4  0.15  0.64   NaN   NaN  0.10  0.64  0.88  0.24   NaN    NaN   NaN   NaN
```

2.8.11 Exploding a list-like column

New in version 0.25.0.

Sometimes the values in a column are list-like.

```
In [135]: keys = ["panda1", "panda2", "panda3"]

In [136]: values = [["eats", "shoots"], ["shoots", "leaves"], ["eats", "leaves"]]

In [137]: df = pd.DataFrame({"keys": keys, "values": values})

In [138]: df
Out[138]:
     keys             values
0  panda1    [eats, shoots]
1  panda2  [shoots, leaves]
2  panda3    [eats, leaves]
```

We can 'explode' the `values` column, transforming each list-like to a separate row, by using *`explode()`*. This will replicate the index values from the original row:

```
In [139]: df["values"].explode()
Out[139]:
0      eats
0    shoots
1    shoots
1    leaves
2      eats
2    leaves
Name: values, dtype: object
```

You can also explode the column in the `DataFrame`.

```
In [140]: df.explode("values")
Out[140]:
     keys  values
0  panda1    eats
0  panda1  shoots
1  panda2  shoots
1  panda2  leaves
2  panda3    eats
2  panda3  leaves
```

`Series.explode()` will replace empty lists with `np.nan` and preserve scalar entries. The dtype of the resulting `Series` is always `object`.

```
In [141]: s = pd.Series([[1, 2, 3], "foo", [], ["a", "b"]])

In [142]: s
Out[142]:
0    [1, 2, 3]
1          foo
2           []
3       [a, b]
dtype: object

In [143]: s.explode()
Out[143]:
0      1
0      2
0      3
1    foo
2    NaN
3      a
3      b
dtype: object
```

Here is a typical usecase. You have comma separated strings in a column and want to expand this.

```
In [144]: df = pd.DataFrame([{"var1": "a,b,c", "var2": 1}, {"var1": "d,e,f", "var2":␣
↪2}])

In [145]: df
Out[145]:
    var1  var2
```

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```
0  a,b,c     1
1  d,e,f     2
```

Creating a long form DataFrame is now straightforward using explode and chained operations

```
In [146]: df.assign(var1=df.var1.str.split(",")).explode("var1")
Out[146]:
  var1  var2
0    a     1
0    b     1
0    c     1
1    d     2
1    e     2
1    f     2
```

2.9 Working with text data

2.9.1 Text data types

New in version 1.0.0.

There are two ways to store text data in pandas:

1. `object` -dtype NumPy array.
2. *`StringDtype`* extension type.

We recommend using *`StringDtype`* to store text data.

Prior to pandas 1.0, `object` dtype was the only option. This was unfortunate for many reasons:

1. You can accidentally store a *mixture* of strings and non-strings in an `object` dtype array. It's better to have a dedicated dtype.
2. `object` dtype breaks dtype-specific operations like *`DataFrame.select_dtypes()`*. There isn't a clear way to select *just* text while excluding non-text but still object-dtype columns.
3. When reading code, the contents of an `object` dtype array is less clear than `'string'`.

Currently, the performance of `object` dtype arrays of strings and *`arrays.StringArray`* are about the same. We expect future enhancements to significantly increase the performance and lower the memory overhead of *`StringArray`*.

Warning: `StringArray` is currently considered experimental. The implementation and parts of the API may change without warning.

For backwards-compatibility, `object` dtype remains the default type we infer a list of strings to

```
In [1]: pd.Series(["a", "b", "c"])
Out[1]:
0    a
1    b
2    c
dtype: object
```

To explicitly request `string` dtype, specify the `dtype`

```
In [2]: pd.Series(["a", "b", "c"], dtype="string")
Out[2]:
0    a
1    b
2    c
dtype: string

In [3]: pd.Series(["a", "b", "c"], dtype=pd.StringDtype())
Out[3]:
0    a
1    b
2    c
dtype: string
```

Or `astype` after the `Series` or `DataFrame` is created

```
In [4]: s = pd.Series(["a", "b", "c"])

In [5]: s
Out[5]:
0    a
1    b
2    c
dtype: object

In [6]: s.astype("string")
Out[6]:
0    a
1    b
2    c
dtype: string
```

Changed in version 1.1.0.

You can also use *StringDtype*/`"string"` as the dtype on non-string data and it will be converted to `string` dtype:

```
In [7]: s = pd.Series(["a", 2, np.nan], dtype="string")

In [8]: s
Out[8]:
0       a
1       2
2    <NA>
dtype: string

In [9]: type(s[1])
Out[9]: str
```

or convert from existing pandas data:

```
In [10]: s1 = pd.Series([1, 2, np.nan], dtype="Int64")

In [11]: s1
Out[11]:
0       1
```

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```
1       2
2    <NA>
dtype: Int64

In [12]: s2 = s1.astype("string")

In [13]: s2
Out[13]:
0       1
1       2
2    <NA>
dtype: string

In [14]: type(s2[0])
Out[14]: str
```

Behavior differences

These are places where the behavior of `StringDtype` objects differ from `object` dtype

1. For `StringDtype`, *string accessor methods* that return **numeric** output will always return a nullable integer dtype, rather than either int or float dtype, depending on the presence of NA values. Methods returning **boolean** output will return a nullable boolean dtype.

```
In [15]: s = pd.Series(["a", None, "b"], dtype="string")

In [16]: s
Out[16]:
0       a
1    <NA>
2       b
dtype: string

In [17]: s.str.count("a")
Out[17]:
0       1
1    <NA>
2       0
dtype: Int64

In [18]: s.dropna().str.count("a")
Out[18]:
0    1
2    0
dtype: Int64
```

   Both outputs are `Int64` dtype. Compare that with object-dtype

```
In [19]: s2 = pd.Series(["a", None, "b"], dtype="object")

In [20]: s2.str.count("a")
Out[20]:
0    1.0
1    NaN
2    0.0
```

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```
dtype: float64

In [21]: s2.dropna().str.count("a")
Out[21]:
0    1
2    0
dtype: int64
```

When NA values are present, the output dtype is float64. Similarly for methods returning boolean values.

```
In [22]: s.str.isdigit()
Out[22]:
0    False
1     <NA>
2    False
dtype: boolean

In [23]: s.str.match("a")
Out[23]:
0     True
1     <NA>
2    False
dtype: boolean
```

2. Some string methods, like *Series.str.decode()* are not available on StringArray because StringArray only holds strings, not bytes.
3. In comparison operations, *arrays.StringArray* and Series backed by a StringArray will return an object with *BooleanDtype*, rather than a bool dtype object. Missing values in a StringArray will propagate in comparison operations, rather than always comparing unequal like numpy.nan.

Everything else that follows in the rest of this document applies equally to string and object dtype.

2.9.2 String methods

Series and Index are equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the str attribute and generally have names matching the equivalent (scalar) built-in string methods:

```
In [24]: s = pd.Series(
   ....:     ["A", "B", "C", "Aaba", "Baca", np.nan, "CABA", "dog", "cat"], dtype=
↪"string"
   ....: )
   ....:

In [25]: s.str.lower()
Out[25]:
0       a
1       b
2       c
3    aaba
4    baca
5    <NA>
6    caba
7     dog
```

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```
8     cat
dtype: string

In [26]: s.str.upper()
Out[26]:
0       A
1       B
2       C
3    AABA
4    BACA
5    <NA>
6    CABA
7     DOG
8     CAT
dtype: string

In [27]: s.str.len()
Out[27]:
0       1
1       1
2       1
3       4
4       4
5    <NA>
6       4
7       3
8       3
dtype: Int64
```

```
In [28]: idx = pd.Index([" jack", "jill ", " jesse ", "frank"])

In [29]: idx.str.strip()
Out[29]: Index(['jack', 'jill', 'jesse', 'frank'], dtype='object')

In [30]: idx.str.lstrip()
Out[30]: Index(['jack', 'jill ', 'jesse ', 'frank'], dtype='object')

In [31]: idx.str.rstrip()
Out[31]: Index([' jack', 'jill', ' jesse', 'frank'], dtype='object')
```

The string methods on Index are especially useful for cleaning up or transforming DataFrame columns. For instance, you may have columns with leading or trailing whitespace:

```
In [32]: df = pd.DataFrame(
   ....:     np.random.randn(3, 2), columns=[" Column A ", " Column B "],␣
↪index=range(3)
   ....: )
   ....:

In [33]: df
Out[33]:
    Column A    Column B
0    0.469112   -0.282863
1   -1.509059   -1.135632
2    1.212112   -0.173215
```

Since `df.columns` is an Index object, we can use the `.str` accessor

```
In [34]: df.columns.str.strip()
Out[34]: Index(['Column A', 'Column B'], dtype='object')

In [35]: df.columns.str.lower()
Out[35]: Index([' column a ', ' column b '], dtype='object')
```

These string methods can then be used to clean up the columns as needed. Here we are removing leading and trailing whitespaces, lower casing all names, and replacing any remaining whitespaces with underscores:

```
In [36]: df.columns = df.columns.str.strip().str.lower().str.replace(" ", "_")

In [37]: df
Out[37]:
   column_a  column_b
0  0.469112 -0.282863
1 -1.509059 -1.135632
2  1.212112 -0.173215
```

Note: If you have a `Series` where lots of elements are repeated (i.e. the number of unique elements in the `Series` is a lot smaller than the length of the `Series`), it can be faster to convert the original `Series` to one of type `category` and then use `.str.<method>` or `.dt.<property>` on that. The performance difference comes from the fact that, for `Series` of type `category`, the string operations are done on the `.categories` and not on each element of the `Series`.

Please note that a `Series` of type `category` with string `.categories` has some limitations in comparison to `Series` of type string (e.g. you can't add strings to each other: `s + " " + s` won't work if `s` is a `Series` of type `category`). Also, `.str` methods which operate on elements of type `list` are not available on such a `Series`.

Warning: Before v.0.25.0, the `.str`-accessor did only the most rudimentary type checks. Starting with v.0.25.0, the type of the Series is inferred and the allowed types (i.e. strings) are enforced more rigorously.

Generally speaking, the `.str` accessor is intended to work only on strings. With very few exceptions, other uses are not supported, and may be disabled at a later point.

2.9.3 Splitting and replacing strings

Methods like `split` return a Series of lists:

```
In [38]: s2 = pd.Series(["a_b_c", "c_d_e", np.nan, "f_g_h"], dtype="string")

In [39]: s2.str.split("_")
Out[39]:
0    [a, b, c]
1    [c, d, e]
2         <NA>
3    [f, g, h]
dtype: object
```

Elements in the split lists can be accessed using `get` or `[]` notation:

```
In [40]: s2.str.split("_").str.get(1)
Out[40]:
```

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```
0       b
1       d
2    <NA>
3       g
dtype: object

In [41]: s2.str.split("_").str[1]
Out[41]:
0       b
1       d
2    <NA>
3       g
dtype: object
```

It is easy to expand this to return a DataFrame using `expand`.

```
In [42]: s2.str.split("_", expand=True)
Out[42]:
      0     1     2
0     a     b     c
1     c     d     e
2  <NA>  <NA>  <NA>
3     f     g     h
```

When original `Series` has *`StringDtype`*, the output columns will all be *`StringDtype`* as well.

It is also possible to limit the number of splits:

```
In [43]: s2.str.split("_", expand=True, n=1)
Out[43]:
      0     1
0     a   b_c
1     c   d_e
2  <NA>  <NA>
3     f   g_h
```

`rsplit` is similar to `split` except it works in the reverse direction, i.e., from the end of the string to the beginning of the string:

```
In [44]: s2.str.rsplit("_", expand=True, n=1)
Out[44]:
      0     1
0   a_b     c
1   c_d     e
2  <NA>  <NA>
3   f_g     h
```

`replace` optionally uses regular expressions:

```
In [45]: s3 = pd.Series(
   ....:     ["A", "B", "C", "Aaba", "Baca", "", np.nan, "CABA", "dog", "cat"],
   ....:     dtype="string",
   ....: )
   ....:

In [46]: s3
Out[46]:
```

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```
0       A
1       B
2       C
3    Aaba
4    Baca
5
6    <NA>
7    CABA
8     dog
9     cat
dtype: string

In [47]: s3.str.replace("^.a|dog", "XX-XX ", case=False, regex=True)
Out[47]:
0           A
1           B
2           C
3    XX-XX ba
4    XX-XX ca
5
6        <NA>
7    XX-XX BA
8      XX-XX
9     XX-XX t
dtype: string
```

Warning: Some caution must be taken when dealing with regular expressions! The current behavior is to treat single character patterns as literal strings, even when `regex` is set to `True`. This behavior is deprecated and will be removed in a future version so that the `regex` keyword is always respected.

Changed in version 1.2.0.

If you want literal replacement of a string (equivalent to `str.replace()`), you can set the optional `regex` parameter to `False`, rather than escaping each character. In this case both `pat` and `repl` must be strings:

```
In [48]: dollars = pd.Series(["12", "-$10", "$10,000"], dtype="string")

# These lines are equivalent
In [49]: dollars.str.replace(r"-\$", "-", regex=True)
Out[49]:
0         12
1        -10
2    $10,000
dtype: string

In [50]: dollars.str.replace("-$", "-", regex=False)
Out[50]:
0         12
1        -10
2    $10,000
dtype: string
```

The `replace` method can also take a callable as replacement. It is called on every `pat` using `re.sub()`. The callable should expect one positional argument (a regex object) and return a string.

```
# Reverse every lowercase alphabetic word
In [51]: pat = r"[a-z]+"

In [52]: def repl(m):
   ....:     return m.group(0)[::-1]
   ....:

In [53]: pd.Series(["foo 123", "bar baz", np.nan], dtype="string").str.replace(
   ....:     pat, repl, regex=True
   ....: )
   ....:
Out[53]:
0    oof 123
1    rab zab
2       <NA>
dtype: string

# Using regex groups
In [54]: pat = r"(?P<one>\w+) (?P<two>\w+) (?P<three>\w+)"

In [55]: def repl(m):
   ....:     return m.group("two").swapcase()
   ....:

In [56]: pd.Series(["Foo Bar Baz", np.nan], dtype="string").str.replace(
   ....:     pat, repl, regex=True
   ....: )
   ....:
Out[56]:
0     bAR
1    <NA>
dtype: string
```

The `replace` method also accepts a compiled regular expression object from `re.compile()` as a pattern. All flags should be included in the compiled regular expression object.

```
In [57]: import re

In [58]: regex_pat = re.compile(r"^.a|dog", flags=re.IGNORECASE)

In [59]: s3.str.replace(regex_pat, "XX-XX ", regex=True)
Out[59]:
0           A
1           B
2           C
3    XX-XX ba
4    XX-XX ca
5
6        <NA>
7    XX-XX BA
8       XX-XX
9     XX-XX t
dtype: string
```

Including a `flags` argument when calling `replace` with a compiled regular expression object will raise a `ValueError`.

```
In [60]: s3.str.replace(regex_pat, 'XX-XX ', flags=re.IGNORECASE)
---------------------------------------------------------------------------
ValueError: case and flags cannot be set when pat is a compiled regex
```

2.9.4 Concatenation

There are several ways to concatenate a `Series` or `Index`, either with itself or others, all based on *`cat()`*, resp. `Index.str.cat`.

Concatenating a single Series into a string

The content of a `Series` (or `Index`) can be concatenated:

```
In [61]: s = pd.Series(["a", "b", "c", "d"], dtype="string")

In [62]: s.str.cat(sep=",")
Out[62]: 'a,b,c,d'
```

If not specified, the keyword `sep` for the separator defaults to the empty string, `sep=''`:

```
In [63]: s.str.cat()
Out[63]: 'abcd'
```

By default, missing values are ignored. Using `na_rep`, they can be given a representation:

```
In [64]: t = pd.Series(["a", "b", np.nan, "d"], dtype="string")

In [65]: t.str.cat(sep=",")
Out[65]: 'a,b,d'

In [66]: t.str.cat(sep=",", na_rep="-")
Out[66]: 'a,b,-,d'
```

Concatenating a Series and something list-like into a Series

The first argument to *`cat()`* can be a list-like object, provided that it matches the length of the calling `Series` (or `Index`).

```
In [67]: s.str.cat(["A", "B", "C", "D"])
Out[67]:
0    aA
1    bB
2    cC
3    dD
dtype: string
```

Missing values on either side will result in missing values in the result as well, *unless* `na_rep` is specified:

```
In [68]: s.str.cat(t)
Out[68]:
0      aa
1      bb
2    <NA>
```

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```
3      dd
dtype: string

In [69]: s.str.cat(t, na_rep="-")
Out[69]:
0    aa
1    bb
2    c-
3    dd
dtype: string
```

Concatenating a Series and something array-like into a Series

The parameter `others` can also be two-dimensional. In this case, the number or rows must match the lengths of the calling `Series` (or `Index`).

```
In [70]: d = pd.concat([t, s], axis=1)

In [71]: s
Out[71]:
0    a
1    b
2    c
3    d
dtype: string

In [72]: d
Out[72]:
      0  1
0     a  a
1     b  b
2  <NA>  c
3     d  d

In [73]: s.str.cat(d, na_rep="-")
Out[73]:
0    aaa
1    bbb
2    c-c
3    ddd
dtype: string
```

Concatenating a Series and an indexed object into a Series, with alignment

For concatenation with a `Series` or `DataFrame`, it is possible to align the indexes before concatenation by setting the `join`-keyword.

```
In [74]: u = pd.Series(["b", "d", "a", "c"], index=[1, 3, 0, 2], dtype="string")

In [75]: s
Out[75]:
0    a
1    b
```

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```
2    c
3    d
dtype: string

In [76]: u
Out[76]:
1    b
3    d
0    a
2    c
dtype: string

In [77]: s.str.cat(u)
Out[77]:
0    aa
1    bb
2    cc
3    dd
dtype: string

In [78]: s.str.cat(u, join="left")
Out[78]:
0    aa
1    bb
2    cc
3    dd
dtype: string
```

Warning: If the `join` keyword is not passed, the method *`cat()`* will currently fall back to the behavior before version 0.23.0 (i.e. no alignment), but a `FutureWarning` will be raised if any of the involved indexes differ, since this default will change to `join='left'` in a future version.

The usual options are available for `join` (one of `'left', 'outer', 'inner', 'right'`). In particular, alignment also means that the different lengths do not need to coincide anymore.

```
In [79]: v = pd.Series(["z", "a", "b", "d", "e"], index=[-1, 0, 1, 3, 4], dtype=
↪"string")

In [80]: s
Out[80]:
0    a
1    b
2    c
3    d
dtype: string

In [81]: v
Out[81]:
-1    z
 0    a
 1    b
 3    d
 4    e
dtype: string
```

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```
In [82]: s.str.cat(v, join="left", na_rep="-")
Out[82]:
0    aa
1    bb
2    c-
3    dd
dtype: string

In [83]: s.str.cat(v, join="outer", na_rep="-")
Out[83]:
-1    -z
 0    aa
 1    bb
 2    c-
 3    dd
 4    -e
dtype: string
```

The same alignment can be used when `others` is a `DataFrame`:

```
In [84]: f = d.loc[[3, 2, 1, 0], :]

In [85]: s
Out[85]:
0    a
1    b
2    c
3    d
dtype: string

In [86]: f
Out[86]:
      0  1
3     d  d
2  <NA>  c
1     b  b
0     a  a

In [87]: s.str.cat(f, join="left", na_rep="-")
Out[87]:
0    aaa
1    bbb
2    c-c
3    ddd
dtype: string
```

Concatenating a Series and many objects into a Series

Several array-like items (specifically: `Series`, `Index`, and 1-dimensional variants of `np.ndarray`) can be combined in a list-like container (including iterators, `dict`-views, etc.).

```
In [88]: s
Out[88]:
0    a
1    b
2    c
3    d
dtype: string

In [89]: u
Out[89]:
1    b
3    d
0    a
2    c
dtype: string

In [90]: s.str.cat([u, u.to_numpy()], join="left")
Out[90]:
0    aab
1    bbd
2    cca
3    ddc
dtype: string
```

All elements without an index (e.g. `np.ndarray`) within the passed list-like must match in length to the calling `Series` (or `Index`), but `Series` and `Index` may have arbitrary length (as long as alignment is not disabled with `join=None`):

```
In [91]: v
Out[91]:
-1    z
 0    a
 1    b
 3    d
 4    e
dtype: string

In [92]: s.str.cat([v, u, u.to_numpy()], join="outer", na_rep="-")
Out[92]:
-1    -z--
 0    aaab
 1    bbbd
 2    c-ca
 3    dddc
 4    -e--
dtype: string
```

If using `join='right'` on a list-like of `others` that contains different indexes, the union of these indexes will be used as the basis for the final concatenation:

```
In [93]: u.loc[[3]]
Out[93]:
```

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```
3    d
dtype: string

In [94]: v.loc[[-1, 0]]
Out[94]:
-1    z
 0    a
dtype: string

In [95]: s.str.cat([u.loc[[3]], v.loc[[-1, 0]]], join="right", na_rep="-")
Out[95]:
-1    --z
 0    a-a
 3    dd-
dtype: string
```

2.9.5 Indexing with `.str`

You can use `[]` notation to directly index by position locations. If you index past the end of the string, the result will be a `NaN`.

```
In [96]: s = pd.Series(
   ....:     ["A", "B", "C", "Aaba", "Baca", np.nan, "CABA", "dog", "cat"], dtype=
↪"string"
   ....: )
   ....:

In [97]: s.str[0]
Out[97]:
0       A
1       B
2       C
3       A
4       B
5    <NA>
6       C
7       d
8       c
dtype: string

In [98]: s.str[1]
Out[98]:
0    <NA>
1    <NA>
2    <NA>
3       a
4       a
5    <NA>
6       A
7       o
8       a
dtype: string
```

2.9.6 Extracting substrings

Extract first match in each subject (extract)

Warning: Before version 0.23, argument `expand` of the `extract` method defaulted to `False`. When `expand=False`, `expand` returns a `Series`, `Index`, or `DataFrame`, depending on the subject and regular expression pattern. When `expand=True`, it always returns a `DataFrame`, which is more consistent and less confusing from the perspective of a user. `expand=True` has been the default since version 0.23.0.

The `extract` method accepts a regular expression with at least one capture group.

Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```
In [99]: pd.Series(
   ....:     ["a1", "b2", "c3"],
   ....:     dtype="string",
   ....: ).str.extract(r"([ab])(\d)", expand=False)
   ....:
Out[99]:
      0     1
0     a     1
1     b     2
2  <NA>  <NA>
```

Elements that do not match return a row filled with `NaN`. Thus, a Series of messy strings can be "converted" into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating `get()` to access tuples or `re.match` objects. The dtype of the result is always object, even if no match is found and the result only contains `NaN`.

Named groups like

```
In [100]: pd.Series(["a1", "b2", "c3"], dtype="string").str.extract(
   .....:     r"(?P<letter>[ab])(?P<digit>\d)", expand=False
   .....: )
   .....:
Out[100]:
  letter digit
0      a     1
1      b     2
2   <NA>  <NA>
```

and optional groups like

```
In [101]: pd.Series(
   .....:     ["a1", "b2", "3"],
   .....:     dtype="string",
   .....: ).str.extract(r"([ab])?(\d)", expand=False)
   .....:
Out[101]:
      0  1
0     a  1
1     b  2
2  <NA>  3
```

can also be used. Note that any capture group names in the regular expression will be used for column names; otherwise capture group numbers will be used.

Extracting a regular expression with one group returns a `DataFrame` with one column if `expand=True`.

```
In [102]: pd.Series(["a1", "b2", "c3"], dtype="string").str.extract(r"[ab](\d)",␣
↪expand=True)
Out[102]:
      0
0     1
1     2
2  <NA>
```

It returns a Series if `expand=False`.

```
In [103]: pd.Series(["a1", "b2", "c3"], dtype="string").str.extract(r"[ab](\d)",␣
↪expand=False)
Out[103]:
0       1
1       2
2    <NA>
dtype: string
```

Calling on an `Index` with a regex with exactly one capture group returns a `DataFrame` with one column if `expand=True`.

```
In [104]: s = pd.Series(["a1", "b2", "c3"], ["A11", "B22", "C33"], dtype="string")

In [105]: s
Out[105]:
A11    a1
B22    b2
C33    c3
dtype: string

In [106]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=True)
Out[106]:
  letter
0      A
1      B
2      C
```

It returns an `Index` if `expand=False`.

```
In [107]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=False)
Out[107]: Index(['A', 'B', 'C'], dtype='object', name='letter')
```

Calling on an `Index` with a regex with more than one capture group returns a `DataFrame` if `expand=True`.

```
In [108]: s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=True)
Out[108]:
  letter   1
0      A  11
1      B  22
2      C  33
```

It raises `ValueError` if `expand=False`.

```
>>> s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=False)
ValueError: only one regex group is supported with Index
```

The table below summarizes the behavior of `extract(expand=False)` (input subject in first column, number of groups in regex in first row)

	1 group	>1 group
Index	Index	ValueError
Series	Series	DataFrame

Extract all matches in each subject (extractall)

Unlike `extract` (which returns only the first match),

```
In [109]: s = pd.Series(["a1a2", "b1", "c1"], index=["A", "B", "C"], dtype="string")

In [110]: s
Out[110]:
A    a1a2
B      b1
C      c1
dtype: string

In [111]: two_groups = "(?P<letter>[a-z])(?P<digit>[0-9])"

In [112]: s.str.extract(two_groups, expand=True)
Out[112]:
  letter digit
A      a     1
B      b     1
C      c     1
```

the `extractall` method returns every match. The result of `extractall` is always a `DataFrame` with a `MultiIndex` on its rows. The last level of the `MultiIndex` is named `match` and indicates the order in the subject.

```
In [113]: s.str.extractall(two_groups)
Out[113]:
        letter digit
  match
A 0          a     1
  1          a     2
B 0          b     1
C 0          c     1
```

When each subject string in the Series has exactly one match,

```
In [114]: s = pd.Series(["a3", "b3", "c2"], dtype="string")

In [115]: s
Out[115]:
0    a3
1    b3
2    c2
dtype: string
```

then `extractall(pat).xs(0, level='match')` gives the same result as `extract(pat)`.

```
In [116]: extract_result = s.str.extract(two_groups, expand=True)

In [117]: extract_result
Out[117]:
  letter digit
0      a     3
1      b     3
2      c     2

In [118]: extractall_result = s.str.extractall(two_groups)

In [119]: extractall_result
Out[119]:
        letter digit
  match
0 0          a     3
1 0          b     3
2 0          c     2

In [120]: extractall_result.xs(0, level="match")
Out[120]:
  letter digit
0      a     3
1      b     3
2      c     2
```

`Index` also supports `.str.extractall`. It returns a `DataFrame` which has the same result as a `Series.str.extractall` with a default index (starts from 0).

```
In [121]: pd.Index(["a1a2", "b1", "c1"]).str.extractall(two_groups)
Out[121]:
        letter digit
  match
0 0          a     1
  1          a     2
1 0          b     1
2 0          c     1

In [122]: pd.Series(["a1a2", "b1", "c1"], dtype="string").str.extractall(two_groups)
Out[122]:
        letter digit
  match
0 0          a     1
  1          a     2
1 0          b     1
2 0          c     1
```

2.9.7 Testing for strings that match or contain a pattern

You can check whether elements contain a pattern:

```
In [123]: pattern = r"[0-9][a-z]"

In [124]: pd.Series(
   .....:     ["1", "2", "3a", "3b", "03c", "4dx"],
   .....:     dtype="string",
   .....: ).str.contains(pattern)
   .....:
Out[124]:
0    False
1    False
2     True
3     True
4     True
5     True
dtype: boolean
```

Or whether elements match a pattern:

```
In [125]: pd.Series(
   .....:     ["1", "2", "3a", "3b", "03c", "4dx"],
   .....:     dtype="string",
   .....: ).str.match(pattern)
   .....:
Out[125]:
0    False
1    False
2     True
3     True
4    False
5     True
dtype: boolean
```

New in version 1.1.0.

```
In [126]: pd.Series(
   .....:     ["1", "2", "3a", "3b", "03c", "4dx"],
   .....:     dtype="string",
   .....: ).str.fullmatch(pattern)
   .....:
Out[126]:
0    False
1    False
2     True
3     True
4    False
5    False
dtype: boolean
```

Note: The distinction between `match`, `fullmatch`, and `contains` is strictness: `fullmatch` tests whether the entire string matches the regular expression; `match` tests whether there is a match of the regular expression that begins at the first character of the string; and `contains` tests whether there is a match of the regular expression at any position within the string.

The corresponding functions in the `re` package for these three match modes are re.fullmatch, re.match, and re.search, respectively.

Methods like `match`, `fullmatch`, `contains`, `startswith`, and `endswith` take an extra `na` argument so missing values can be considered True or False:

```
In [127]: s4 = pd.Series(
   .....:     ["A", "B", "C", "Aaba", "Baca", np.nan, "CABA", "dog", "cat"], dtype=
↪"string"
   .....: )
   .....:

In [128]: s4.str.contains("A", na=False)
Out[128]:
0     True
1    False
2    False
3     True
4    False
5    False
6     True
7    False
8    False
dtype: boolean
```

2.9.8 Creating indicator variables

You can extract dummy variables from string columns. For example if they are separated by a `'|'`:

```
In [129]: s = pd.Series(["a", "a|b", np.nan, "a|c"], dtype="string")

In [130]: s.str.get_dummies(sep="|")
Out[130]:
   a  b  c
0  1  0  0
1  1  1  0
2  0  0  0
3  1  0  1
```

String `Index` also supports `get_dummies` which returns a `MultiIndex`.

```
In [131]: idx = pd.Index(["a", "a|b", np.nan, "a|c"])

In [132]: idx.str.get_dummies(sep="|")
Out[132]:
MultiIndex([(1, 0, 0),
            (1, 1, 0),
            (0, 0, 0),
            (1, 0, 1)],
           names=['a', 'b', 'c'])
```

See also *get_dummies()*.

2.9.9 Method summary

Method	Description
cat()	Concatenate strings
split()	Split strings on delimiter
rsplit()	Split strings on delimiter working from the end of the string
get()	Index into each element (retrieve i-th element)
join()	Join strings in each element of the Series with passed separator
get_dummies()	Split strings on the delimiter returning DataFrame of dummy variables
contains()	Return boolean array if each string contains pattern/regex
replace()	Replace occurrences of pattern/regex/string with some other string or the return value of a callable given the occurrence
repeat()	Duplicate values (`s.str.repeat(3)` equivalent to `x * 3`)
pad()	Add whitespace to left, right, or both sides of strings
center()	Equivalent to `str.center`
ljust()	Equivalent to `str.ljust`
rjust()	Equivalent to `str.rjust`
zfill()	Equivalent to `str.zfill`
wrap()	Split long strings into lines with length less than a given width
slice()	Slice each string in the Series
slice_replace()	Replace slice in each string with passed value
count()	Count occurrences of pattern
startswith()	Equivalent to `str.startswith(pat)` for each element
endswith()	Equivalent to `str.endswith(pat)` for each element
findall()	Compute list of all occurrences of pattern/regex for each string
match()	Call `re.match` on each element, returning matched groups as list
extract()	Call `re.search` on each element, returning DataFrame with one row for each element and one column for each regex capture group
extractall()	Call `re.findall` on each element, returning DataFrame with one row for each match and one column for each regex capture group
len()	Compute string lengths
strip()	Equivalent to `str.strip`
rstrip()	Equivalent to `str.rstrip`
lstrip()	Equivalent to `str.lstrip`
partition()	Equivalent to `str.partition`
rpartition()	Equivalent to `str.rpartition`
lower()	Equivalent to `str.lower`
casefold()	Equivalent to `str.casefold`
upper()	Equivalent to `str.upper`
find()	Equivalent to `str.find`
rfind()	Equivalent to `str.rfind`
index()	Equivalent to `str.index`
rindex()	Equivalent to `str.rindex`
capitalize()	Equivalent to `str.capitalize`
swapcase()	Equivalent to `str.swapcase`
normalize()	Return Unicode normal form. Equivalent to `unicodedata.normalize`
translate()	Equivalent to `str.translate`
isalnum()	Equivalent to `str.isalnum`
isalpha()	Equivalent to `str.isalpha`
isdigit()	Equivalent to `str.isdigit`
isspace()	Equivalent to `str.isspace`

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Table 2 – continued from previous page

Method	Description
islower()	Equivalent to `str.islower`
isupper()	Equivalent to `str.isupper`
istitle()	Equivalent to `str.istitle`
isnumeric()	Equivalent to `str.isnumeric`
isdecimal()	Equivalent to `str.isdecimal`

2.10 Working with missing data

In this section, we will discuss missing (also referred to as NA) values in pandas.

Note: The choice of using `NaN` internally to denote missing data was largely for simplicity and performance reasons. Starting from pandas 1.0, some optional data types start experimenting with a native `NA` scalar using a mask-based approach. See *here* for more.

See the *cookbook* for some advanced strategies.

2.10.1 Values considered "missing"

As data comes in many shapes and forms, pandas aims to be flexible with regard to handling missing data. While `NaN` is the default missing value marker for reasons of computational speed and convenience, we need to be able to easily detect this value with data of different types: floating point, integer, boolean, and general object. In many cases, however, the Python `None` will arise and we wish to also consider that "missing" or "not available" or "NA".

Note: If you want to consider `inf` and `-inf` to be "NA" in computations, you can set `pandas.options.mode.use_inf_as_na = True`.

```
In [1]: df = pd.DataFrame(
   ...:     np.random.randn(5, 3),
   ...:     index=["a", "c", "e", "f", "h"],
   ...:     columns=["one", "two", "three"],
   ...: )
   ...:

In [2]: df["four"] = "bar"

In [3]: df["five"] = df["one"] > 0

In [4]: df
Out[4]:
        one       two     three four   five
a  0.469112 -0.282863 -1.509059  bar   True
c -1.135632  1.212112 -0.173215  bar  False
e  0.119209 -1.044236 -0.861849  bar   True
f -2.104569 -0.494929  1.071804  bar  False
h  0.721555 -0.706771 -1.039575  bar   True

In [5]: df2 = df.reindex(["a", "b", "c", "d", "e", "f", "g", "h"])
```

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```
In [6]: df2
Out[6]:
        one       two     three four   five
a  0.469112 -0.282863 -1.509059  bar   True
b       NaN       NaN       NaN  NaN    NaN
c -1.135632  1.212112 -0.173215  bar  False
d       NaN       NaN       NaN  NaN    NaN
e  0.119209 -1.044236 -0.861849  bar   True
f -2.104569 -0.494929  1.071804  bar  False
g       NaN       NaN       NaN  NaN    NaN
h  0.721555 -0.706771 -1.039575  bar   True
```

To make detecting missing values easier (and across different array dtypes), pandas provides the *isna()* and *notna()* functions, which are also methods on Series and DataFrame objects:

```
In [7]: df2["one"]
Out[7]:
a    0.469112
b         NaN
c   -1.135632
d         NaN
e    0.119209
f   -2.104569
g         NaN
h    0.721555
Name: one, dtype: float64

In [8]: pd.isna(df2["one"])
Out[8]:
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool

In [9]: df2["four"].notna()
Out[9]:
a     True
b    False
c     True
d    False
e     True
f     True
g    False
h     True
Name: four, dtype: bool

In [10]: df2.isna()
Out[10]:
     one    two  three   four   five
a  False  False  False  False  False
b   True   True   True   True   True
```

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```
c  False  False  False  False  False
d   True   True   True   True   True
e  False  False  False  False  False
f  False  False  False  False  False
g   True   True   True   True   True
h  False  False  False  False  False
```

Warning: One has to be mindful that in Python (and NumPy), the `nan`'s don't compare equal, but `None`'s **do**. Note that pandas/NumPy uses the fact that `np.nan != np.nan`, and treats `None` like `np.nan`.

```
In [11]: None == None  # noqa: E711
Out[11]: True

In [12]: np.nan == np.nan
Out[12]: False
```

So as compared to above, a scalar equality comparison versus a `None/np.nan` doesn't provide useful information.

```
In [13]: df2["one"] == np.nan
Out[13]:
a    False
b    False
c    False
d    False
e    False
f    False
g    False
h    False
Name: one, dtype: bool
```

Integer dtypes and missing data

Because `NaN` is a float, a column of integers with even one missing values is cast to floating-point dtype (see *Support for integer NA* for more). pandas provides a nullable integer array, which can be used by explicitly requesting the dtype:

```
In [14]: pd.Series([1, 2, np.nan, 4], dtype=pd.Int64Dtype())
Out[14]:
0       1
1       2
2    <NA>
3       4
dtype: Int64
```

Alternatively, the string alias `dtype='Int64'` (note the capital `"I"`) can be used.

See *Nullable integer data type* for more.

Datetimes

For datetime64[ns] types, `NaT` represents missing values. This is a pseudo-native sentinel value that can be represented by NumPy in a singular dtype (datetime64[ns]). pandas objects provide compatibility between `NaT` and `NaN`.

```
In [15]: df2 = df.copy()

In [16]: df2["timestamp"] = pd.Timestamp("20120101")

In [17]: df2
Out[17]:
        one       two     three four   five  timestamp
a  0.469112 -0.282863 -1.509059  bar   True 2012-01-01
c -1.135632  1.212112 -0.173215  bar  False 2012-01-01
e  0.119209 -1.044236 -0.861849  bar   True 2012-01-01
f -2.104569 -0.494929  1.071804  bar  False 2012-01-01
h  0.721555 -0.706771 -1.039575  bar   True 2012-01-01

In [18]: df2.loc[["a", "c", "h"], ["one", "timestamp"]] = np.nan

In [19]: df2
Out[19]:
        one       two     three four   five  timestamp
a       NaN -0.282863 -1.509059  bar   True        NaT
c       NaN  1.212112 -0.173215  bar  False        NaT
e  0.119209 -1.044236 -0.861849  bar   True 2012-01-01
f -2.104569 -0.494929  1.071804  bar  False 2012-01-01
h       NaN -0.706771 -1.039575  bar   True        NaT

In [20]: df2.dtypes.value_counts()
Out[20]:
float64           3
bool              1
datetime64[ns]    1
object            1
dtype: int64
```

2.10.2 Inserting missing data

You can insert missing values by simply assigning to containers. The actual missing value used will be chosen based on the dtype.

For example, numeric containers will always use `NaN` regardless of the missing value type chosen:

```
In [21]: s = pd.Series([1, 2, 3])

In [22]: s.loc[0] = None

In [23]: s
Out[23]:
0    NaN
1    2.0
2    3.0
dtype: float64
```

Likewise, datetime containers will always use `NaT`.

For object containers, pandas will use the value given:

```
In [24]: s = pd.Series(["a", "b", "c"])

In [25]: s.loc[0] = None

In [26]: s.loc[1] = np.nan

In [27]: s
Out[27]:
0    None
1     NaN
2       c
dtype: object
```

2.10.3 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

```
In [28]: a
Out[28]:
        one       two
a       NaN -0.282863
c       NaN  1.212112
e  0.119209 -1.044236
f -2.104569 -0.494929
h -2.104569 -0.706771

In [29]: b
Out[29]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h       NaN -0.706771 -1.039575

In [30]: a + b
Out[30]:
        one  three       two
a       NaN    NaN -0.565727
c       NaN    NaN  2.424224
e  0.238417    NaN -2.088472
f -4.209138    NaN -0.989859
h       NaN    NaN -1.413542
```

The descriptive statistics and computational methods discussed in the *data structure overview* (and listed *here* and *here*) are all written to account for missing data. For example:

- When summing data, NA (missing) values will be treated as zero.
- If the data are all NA, the result will be 0.
- Cumulative methods like `cumsum()` and `cumprod()` ignore NA values by default, but preserve them in the resulting arrays. To override this behaviour and include NA values, use `skipna=False`.

```
In [31]: df
Out[31]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h       NaN -0.706771 -1.039575

In [32]: df["one"].sum()
Out[32]: -1.9853605075978744

In [33]: df.mean(1)
Out[33]:
a   -0.895961
c    0.519449
e   -0.595625
f   -0.509232
h   -0.873173
dtype: float64

In [34]: df.cumsum()
Out[34]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  0.929249 -1.682273
e  0.119209 -0.114987 -2.544122
f -1.985361 -0.609917 -1.472318
h       NaN -1.316688 -2.511893

In [35]: df.cumsum(skipna=False)
Out[35]:
   one       two     three
a  NaN -0.282863 -1.509059
c  NaN  0.929249 -1.682273
e  NaN -0.114987 -2.544122
f  NaN -0.609917 -1.472318
h  NaN -1.316688 -2.511893
```

2.10.4 Sum/prod of empties/nans

Warning: This behavior is now standard as of v0.22.0 and is consistent with the default in `numpy`; previously sum/prod of all-NA or empty Series/DataFrames would return NaN. See *v0.22.0 whatsnew* for more.

The sum of an empty or all-NA Series or column of a DataFrame is 0.

```
In [36]: pd.Series([np.nan]).sum()
Out[36]: 0.0

In [37]: pd.Series([], dtype="float64").sum()
Out[37]: 0.0
```

The product of an empty or all-NA Series or column of a DataFrame is 1.

```
In [38]: pd.Series([np.nan]).prod()
Out[38]: 1.0

In [39]: pd.Series([], dtype="float64").prod()
Out[39]: 1.0
```

2.10.5 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example:

```
In [40]: df
Out[40]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h       NaN -0.706771 -1.039575

In [41]: df.groupby("one").mean()
Out[41]:
                two     three
one
-2.104569 -0.494929  1.071804
 0.119209 -1.044236 -0.861849
```

See the groupby section *here* for more information.

Cleaning / filling missing data

pandas objects are equipped with various data manipulation methods for dealing with missing data.

2.10.6 Filling missing values: fillna

`fillna()` can "fill in" NA values with non-NA data in a couple of ways, which we illustrate:

Replace NA with a scalar value

```
In [42]: df2
Out[42]:
        one       two     three four   five  timestamp
a       NaN -0.282863 -1.509059  bar   True        NaT
c       NaN  1.212112 -0.173215  bar  False        NaT
e  0.119209 -1.044236 -0.861849  bar   True 2012-01-01
f -2.104569 -0.494929  1.071804  bar  False 2012-01-01
h       NaN -0.706771 -1.039575  bar   True        NaT

In [43]: df2.fillna(0)
Out[43]:
        one       two     three four   five            timestamp
a  0.000000 -0.282863 -1.509059  bar   True                    0
c  0.000000  1.212112 -0.173215  bar  False                    0
e  0.119209 -1.044236 -0.861849  bar   True  2012-01-01 00:00:00
f -2.104569 -0.494929  1.071804  bar  False  2012-01-01 00:00:00
```

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```
h  0.000000 -0.706771 -1.039575  bar   True                    0

In [44]: df2["one"].fillna("missing")
Out[44]:
a     missing
c     missing
e    0.119209
f   -2.104569
h     missing
Name: one, dtype: object
```

Fill gaps forward or backward

Using the same filling arguments as *reindexing*, we can propagate non-NA values forward or backward:

```
In [45]: df
Out[45]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h       NaN -0.706771 -1.039575

In [46]: df.fillna(method="pad")
Out[46]:
        one       two     three
a       NaN -0.282863 -1.509059
c       NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h -2.104569 -0.706771 -1.039575
```

Limit the amount of filling

If we only want consecutive gaps filled up to a certain number of data points, we can use the `limit` keyword:

```
In [47]: df
Out[47]:
   one       two     three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN       NaN       NaN
f  NaN       NaN       NaN
h  NaN -0.706771 -1.039575

In [48]: df.fillna(method="pad", limit=1)
Out[48]:
   one       two     three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN  1.212112 -0.173215
f  NaN       NaN       NaN
h  NaN -0.706771 -1.039575
```

To remind you, these are the available filling methods:

Method	Action
pad / ffill	Fill values forward
bfill / backfill	Fill values backward

With time series data, using pad/ffill is extremely common so that the "last known value" is available at every time point.

ffill() is equivalent to `fillna(method='ffill')` and *bfill()* is equivalent to `fillna(method='bfill')`

2.10.7 Filling with a PandasObject

You can also fillna using a dict or Series that is alignable. The labels of the dict or index of the Series must match the columns of the frame you wish to fill. The use case of this is to fill a DataFrame with the mean of that column.

```
In [49]: dff = pd.DataFrame(np.random.randn(10, 3), columns=list("ABC"))

In [50]: dff.iloc[3:5, 0] = np.nan

In [51]: dff.iloc[4:6, 1] = np.nan

In [52]: dff.iloc[5:8, 2] = np.nan

In [53]: dff
Out[53]:
          A         B         C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3       NaN  0.577046 -1.715002
4       NaN       NaN -1.157892
5 -1.344312       NaN       NaN
6 -0.109050  1.643563       NaN
7  0.357021 -0.674600       NaN
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960

In [54]: dff.fillna(dff.mean())
Out[54]:
          A         B         C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3 -0.140857  0.577046 -1.715002
4 -0.140857 -0.401419 -1.157892
5 -1.344312 -0.401419 -0.293543
6 -0.109050  1.643563 -0.293543
7  0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960

In [55]: dff.fillna(dff.mean()["B":"C"])
Out[55]:
          A         B         C
0  0.271860 -0.424972  0.567020
```

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```
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3       NaN  0.577046 -1.715002
4       NaN -0.401419 -1.157892
5 -1.344312 -0.401419 -0.293543
6 -0.109050  1.643563 -0.293543
7  0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960
```

Same result as above, but is aligning the 'fill' value which is a Series in this case.

```
In [56]: dff.where(pd.notna(dff), dff.mean(), axis="columns")
Out[56]:
          A         B         C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3 -0.140857  0.577046 -1.715002
4 -0.140857 -0.401419 -1.157892
5 -1.344312 -0.401419 -0.293543
6 -0.109050  1.643563 -0.293543
7  0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960
```

2.10.8 Dropping axis labels with missing data: dropna

You may wish to simply exclude labels from a data set which refer to missing data. To do this, use *dropna()*:

```
In [57]: df
Out[57]:
   one       two     three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN  0.000000  0.000000
f  NaN  0.000000  0.000000
h  NaN -0.706771 -1.039575

In [58]: df.dropna(axis=0)
Out[58]:
Empty DataFrame
Columns: [one, two, three]
Index: []

In [59]: df.dropna(axis=1)
Out[59]:
        two     three
a -0.282863 -1.509059
c  1.212112 -0.173215
e  0.000000  0.000000
f  0.000000  0.000000
h -0.706771 -1.039575
```

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```
In [60]: df["one"].dropna()
Out[60]: Series([], Name: one, dtype: float64)
```

An equivalent *dropna()* is available for Series. DataFrame.dropna has considerably more options than Series.dropna, which can be examined *in the API*.

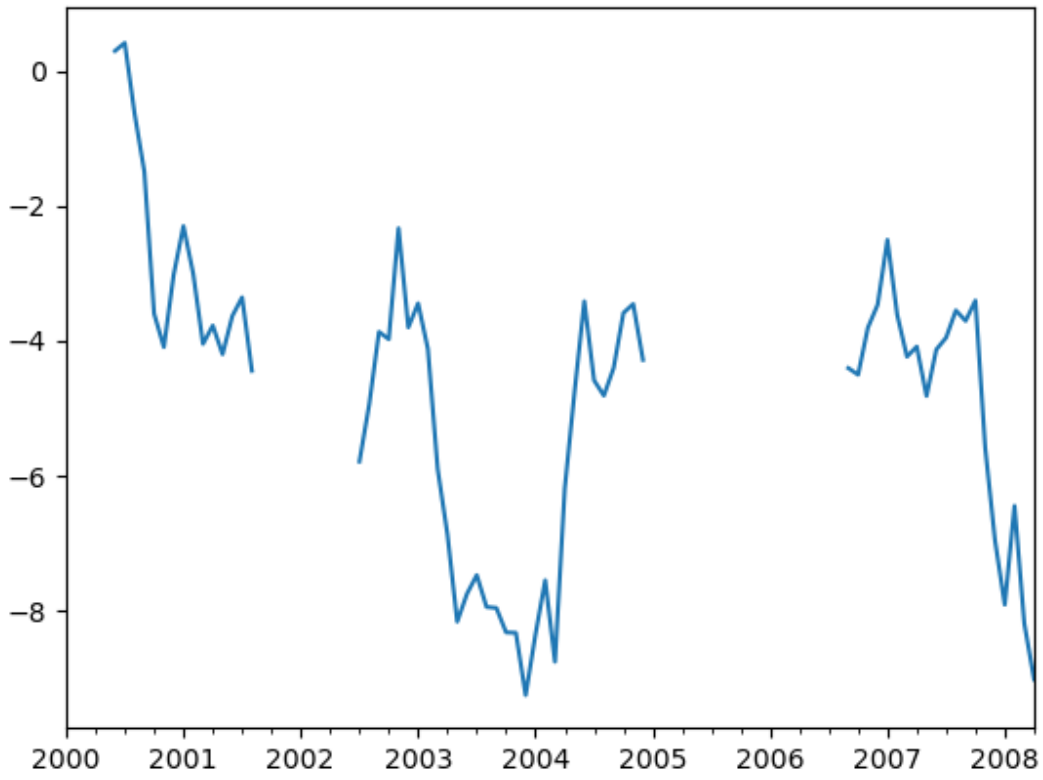
2.10.9 Interpolation

Both Series and DataFrame objects have *interpolate()* that, by default, performs linear interpolation at missing data points.

```
In [61]: ts
Out[61]:
2000-01-31    0.469112
2000-02-29         NaN
2000-03-31         NaN
2000-04-28         NaN
2000-05-31         NaN
                ...
2007-12-31   -6.950267
2008-01-31   -7.904475
2008-02-29   -6.441779
2008-03-31   -8.184940
2008-04-30   -9.011531
Freq: BM, Length: 100, dtype: float64

In [62]: ts.count()
Out[62]: 66

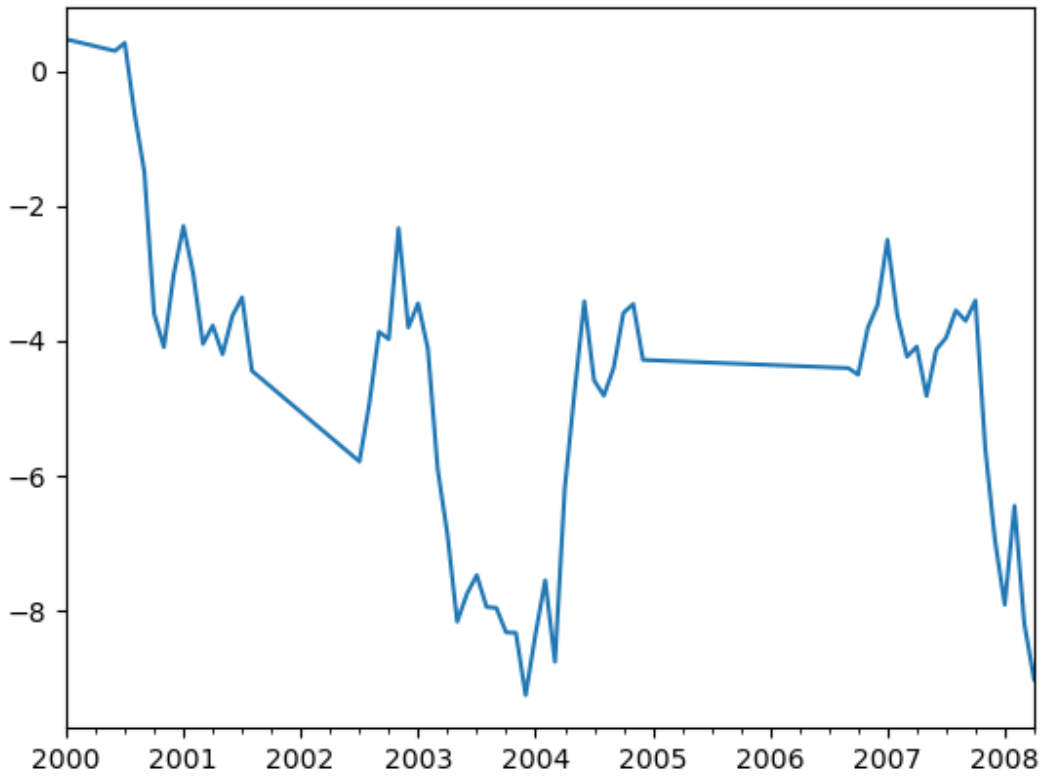
In [63]: ts.plot()
Out[63]: <AxesSubplot:>
```




```
In [64]: ts.interpolate()
Out[64]:
2000-01-31    0.469112
2000-02-29    0.434469
2000-03-31    0.399826
2000-04-28    0.365184
2000-05-31    0.330541
                ...
2007-12-31   -6.950267
2008-01-31   -7.904475
2008-02-29   -6.441779
2008-03-31   -8.184940
2008-04-30   -9.011531
Freq: BM, Length: 100, dtype: float64

In [65]: ts.interpolate().count()
Out[65]: 100

In [66]: ts.interpolate().plot()
Out[66]: <AxesSubplot:>
```



Index aware interpolation is available via the `method` keyword:

```
In [67]: ts2
Out[67]:
2000-01-31    0.469112
2000-02-29         NaN
2002-07-31   -5.785037
2005-01-31         NaN
2008-04-30   -9.011531
dtype: float64

In [68]: ts2.interpolate()
Out[68]:
2000-01-31    0.469112
2000-02-29   -2.657962
2002-07-31   -5.785037
2005-01-31   -7.398284
2008-04-30   -9.011531
dtype: float64

In [69]: ts2.interpolate(method="time")
Out[69]:
2000-01-31    0.469112
2000-02-29    0.270241
2002-07-31   -5.785037
```

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```
2005-01-31   -7.190866
2008-04-30   -9.011531
dtype: float64
```

For a floating-point index, use `method='values'`:

```
In [70]: ser
Out[70]:
0.0      0.0
1.0      NaN
10.0    10.0
dtype: float64

In [71]: ser.interpolate()
Out[71]:
0.0      0.0
1.0      5.0
10.0    10.0
dtype: float64

In [72]: ser.interpolate(method="values")
Out[72]:
0.0      0.0
1.0      1.0
10.0    10.0
dtype: float64
```

You can also interpolate with a DataFrame:

```
In [73]: df = pd.DataFrame(
   ....:     {
   ....:         "A": [1, 2.1, np.nan, 4.7, 5.6, 6.8],
   ....:         "B": [0.25, np.nan, np.nan, 4, 12.2, 14.4],
   ....:     }
   ....: )
   ....:

In [74]: df
Out[74]:
     A      B
0  1.0   0.25
1  2.1    NaN
2  NaN    NaN
3  4.7   4.00
4  5.6  12.20
5  6.8  14.40

In [75]: df.interpolate()
Out[75]:
     A      B
0  1.0   0.25
1  2.1   1.50
2  3.4   2.75
3  4.7   4.00
4  5.6  12.20
5  6.8  14.40
```

The `method` argument gives access to fancier interpolation methods. If you have scipy installed, you can pass the name of a 1-d interpolation routine to `method`. You'll want to consult the full scipy interpolation documentation and reference guide for details. The appropriate interpolation method will depend on the type of data you are working with.

- If you are dealing with a time series that is growing at an increasing rate, `method='quadratic'` may be appropriate.
- If you have values approximating a cumulative distribution function, then `method='pchip'` should work well.
- To fill missing values with goal of smooth plotting, consider `method='akima'`.

Warning: These methods require `scipy`.

```
In [76]: df.interpolate(method="barycentric")
Out[76]:
      A       B
0  1.00   0.250
1  2.10  -7.660
2  3.53  -4.515
3  4.70   4.000
4  5.60  12.200
5  6.80  14.400

In [77]: df.interpolate(method="pchip")
Out[77]:
          A          B
0  1.00000   0.250000
1  2.10000   0.672808
2  3.43454   1.928950
3  4.70000   4.000000
4  5.60000  12.200000
5  6.80000  14.400000

In [78]: df.interpolate(method="akima")
Out[78]:
          A          B
0  1.000000   0.250000
1  2.100000  -0.873316
2  3.406667   0.320034
3  4.700000   4.000000
4  5.600000  12.200000
5  6.800000  14.400000
```

When interpolating via a polynomial or spline approximation, you must also specify the degree or order of the approximation:

```
In [79]: df.interpolate(method="spline", order=2)
Out[79]:
          A          B
0  1.000000   0.250000
1  2.100000  -0.428598
2  3.404545   1.206900
3  4.700000   4.000000
4  5.600000  12.200000
```

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```
5  6.800000  14.400000

In [80]: df.interpolate(method="polynomial", order=2)
Out[80]:
          A          B
0  1.000000   0.250000
1  2.100000  -2.703846
2  3.451351  -1.453846
3  4.700000   4.000000
4  5.600000  12.200000
5  6.800000  14.400000
```

Compare several methods:

```
In [81]: np.random.seed(2)

In [82]: ser = pd.Series(np.arange(1, 10.1, 0.25) ** 2 + np.random.randn(37))

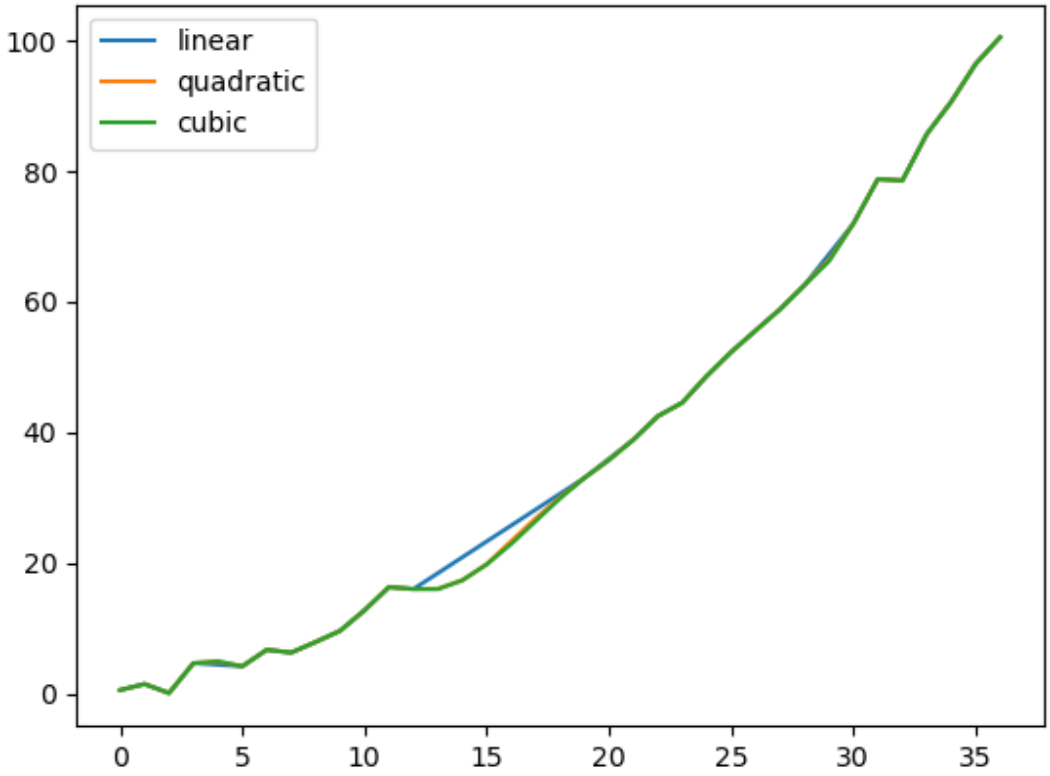
In [83]: missing = np.array([4, 13, 14, 15, 16, 17, 18, 20, 29])

In [84]: ser[missing] = np.nan

In [85]: methods = ["linear", "quadratic", "cubic"]

In [86]: df = pd.DataFrame({m: ser.interpolate(method=m) for m in methods})

In [87]: df.plot()
Out[87]: <AxesSubplot:>
```



Another use case is interpolation at *new* values. Suppose you have 100 observations from some distribution. And let's suppose that you're particularly interested in what's happening around the middle. You can mix pandas' `reindex` and `interpolate` methods to interpolate at the new values.

```
In [88]: ser = pd.Series(np.sort(np.random.uniform(size=100)))

# interpolate at new_index
In [89]: new_index = ser.index.union(pd.Index([49.25, 49.5, 49.75, 50.25, 50.5, 50.
↪75]))

In [90]: interp_s = ser.reindex(new_index).interpolate(method="pchip")

In [91]: interp_s[49:51]
Out[91]:
49.00    0.471410
49.25    0.476841
49.50    0.481780
49.75    0.485998
50.00    0.489266
50.25    0.491814
50.50    0.493995
50.75    0.495763
51.00    0.497074
dtype: float64
```

Interpolation limits

Like other pandas fill methods, *interpolate()* accepts a `limit` keyword argument. Use this argument to limit the number of consecutive `NaN` values filled since the last valid observation:

```
In [92]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, np.nan, 13, np.nan, np.
↪nan])

In [93]: ser
Out[93]:
0     NaN
1     NaN
2     5.0
3     NaN
4     NaN
5     NaN
6    13.0
7     NaN
8     NaN
dtype: float64

# fill all consecutive values in a forward direction
In [94]: ser.interpolate()
Out[94]:
0     NaN
1     NaN
2     5.0
3     7.0
4     9.0
5    11.0
6    13.0
7    13.0
8    13.0
dtype: float64

# fill one consecutive value in a forward direction
In [95]: ser.interpolate(limit=1)
Out[95]:
0     NaN
1     NaN
2     5.0
3     7.0
4     NaN
5     NaN
6    13.0
7    13.0
8     NaN
dtype: float64
```

By default, `NaN` values are filled in a `forward` direction. Use `limit_direction` parameter to fill `backward` or from `both` directions.

```
# fill one consecutive value backwards
In [96]: ser.interpolate(limit=1, limit_direction="backward")
Out[96]:
0     NaN
1     5.0
2     5.0
```

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```
3     NaN
4     NaN
5    11.0
6    13.0
7     NaN
8     NaN
dtype: float64

# fill one consecutive value in both directions
In [97]: ser.interpolate(limit=1, limit_direction="both")
Out[97]:
0     NaN
1     5.0
2     5.0
3     7.0
4     NaN
5    11.0
6    13.0
7    13.0
8     NaN
dtype: float64

# fill all consecutive values in both directions
In [98]: ser.interpolate(limit_direction="both")
Out[98]:
0     5.0
1     5.0
2     5.0
3     7.0
4     9.0
5    11.0
6    13.0
7    13.0
8    13.0
dtype: float64
```

By default, `NaN` values are filled whether they are inside (surrounded by) existing valid values, or outside existing valid values. The `limit_area` parameter restricts filling to either inside or outside values.

```
# fill one consecutive inside value in both directions
In [99]: ser.interpolate(limit_direction="both", limit_area="inside", limit=1)
Out[99]:
0     NaN
1     NaN
2     5.0
3     7.0
4     NaN
5    11.0
6    13.0
7     NaN
8     NaN
dtype: float64

# fill all consecutive outside values backward
In [100]: ser.interpolate(limit_direction="backward", limit_area="outside")
Out[100]:
```

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```
0     5.0
1     5.0
2     5.0
3     NaN
4     NaN
5     NaN
6    13.0
7     NaN
8     NaN
dtype: float64

# fill all consecutive outside values in both directions
In [101]: ser.interpolate(limit_direction="both", limit_area="outside")
Out[101]:
0     5.0
1     5.0
2     5.0
3     NaN
4     NaN
5     NaN
6    13.0
7    13.0
8    13.0
dtype: float64
```

2.10.10 Replacing generic values

Often times we want to replace arbitrary values with other values.

replace() in Series and *replace()* in DataFrame provides an efficient yet flexible way to perform such replacements.

For a Series, you can replace a single value or a list of values by another value:

```
In [102]: ser = pd.Series([0.0, 1.0, 2.0, 3.0, 4.0])

In [103]: ser.replace(0, 5)
Out[103]:
0    5.0
1    1.0
2    2.0
3    3.0
4    4.0
dtype: float64
```

You can replace a list of values by a list of other values:

```
In [104]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
Out[104]:
0    4.0
1    3.0
2    2.0
3    1.0
4    0.0
dtype: float64
```

You can also specify a mapping dict:

```
In [105]: ser.replace({0: 10, 1: 100})
Out[105]:
0     10.0
1    100.0
2      2.0
3      3.0
4      4.0
dtype: float64
```

For a DataFrame, you can specify individual values by column:

```
In [106]: df = pd.DataFrame({"a": [0, 1, 2, 3, 4], "b": [5, 6, 7, 8, 9]})

In [107]: df.replace({"a": 0, "b": 5}, 100)
Out[107]:
     a    b
0  100  100
1    1    6
2    2    7
3    3    8
4    4    9
```

Instead of replacing with specified values, you can treat all given values as missing and interpolate over them:

```
In [108]: ser.replace([1, 2, 3], method="pad")
Out[108]:
0    0.0
1    0.0
2    0.0
3    0.0
4    4.0
dtype: float64
```

2.10.11 String/regular expression replacement

Note: Python strings prefixed with the `r` character such as `r'hello world'` are so-called "raw" strings. They have different semantics regarding backslashes than strings without this prefix. Backslashes in raw strings will be interpreted as an escaped backslash, e.g., `r'\' == '\\'`. You should read about them if this is unclear.

Replace the '.' with `NaN` (str -> str):

```
In [109]: d = {"a": list(range(4)), "b": list("ab.."), "c": ["a", "b", np.nan, "d"]}

In [110]: df = pd.DataFrame(d)

In [111]: df.replace(".", np.nan)
Out[111]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

Now do it with a regular expression that removes surrounding whitespace (regex -> regex):

```
In [112]: df.replace(r"\s*\.\s*", np.nan, regex=True)
Out[112]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

Replace a few different values (list -> list):

```
In [113]: df.replace(["a", "."], ["b", np.nan])
Out[113]:
   a    b    c
0  0    b    b
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

list of regex -> list of regex:

```
In [114]: df.replace([r"\.", r"(a)"], ["dot", r"\1stuff"], regex=True)
Out[114]:
   a       b       c
0  0  astuff  astuff
1  1       b       b
2  2     dot     NaN
3  3     dot       d
```

Only search in column `'b'` (dict -> dict):

```
In [115]: df.replace({"b": "."}, {"b": np.nan})
Out[115]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

Same as the previous example, but use a regular expression for searching instead (dict of regex -> dict):

```
In [116]: df.replace({"b": r"\s*\.\s*"}, {"b": np.nan}, regex=True)
Out[116]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

You can pass nested dictionaries of regular expressions that use `regex=True`:

```
In [117]: df.replace({"b": {"b": r""}}, regex=True)
Out[117]:
   a  b    c
0  0  a    a
1  1       b
```

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```
2  2  .  NaN
3  3  .    d
```

Alternatively, you can pass the nested dictionary like so:

```
In [118]: df.replace(regex={"b": {r"\s*\.\s*": np.nan}})
Out[118]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  NaN  NaN
3  3  NaN    d
```

You can also use the group of a regular expression match when replacing (dict of regex -> dict of regex), this works for lists as well.

```
In [119]: df.replace({"b": r"\s*(\.)\s*"}, {"b": r"\1ty"}, regex=True)
Out[119]:
   a    b    c
0  0    a    a
1  1    b    b
2  2  .ty  NaN
3  3  .ty    d
```

You can pass a list of regular expressions, of which those that match will be replaced with a scalar (list of regex -> regex).

```
In [120]: df.replace([r"\s*\.\s*", r"a|b"], np.nan, regex=True)
Out[120]:
   a   b    c
0  0 NaN  NaN
1  1 NaN  NaN
2  2 NaN  NaN
3  3 NaN    d
```

All of the regular expression examples can also be passed with the `to_replace` argument as the `regex` argument. In this case the `value` argument must be passed explicitly by name or `regex` must be a nested dictionary. The previous example, in this case, would then be:

```
In [121]: df.replace(regex=[r"\s*\.\s*", r"a|b"], value=np.nan)
Out[121]:
   a   b    c
0  0 NaN  NaN
1  1 NaN  NaN
2  2 NaN  NaN
3  3 NaN    d
```

This can be convenient if you do not want to pass `regex=True` every time you want to use a regular expression.

Note: Anywhere in the above `replace` examples that you see a regular expression a compiled regular expression is valid as well.

2.10.12 Numeric replacement

replace() is similar to *fillna()*.

```
In [122]: df = pd.DataFrame(np.random.randn(10, 2))

In [123]: df[np.random.rand(df.shape[0]) > 0.5] = 1.5

In [124]: df.replace(1.5, np.nan)
Out[124]:
          0         1
0 -0.844214 -1.021415
1  0.432396 -0.323580
2  0.423825  0.799180
3  1.262614  0.751965
4       NaN       NaN
5       NaN       NaN
6 -0.498174 -1.060799
7  0.591667 -0.183257
8  1.019855 -1.482465
9       NaN       NaN
```

Replacing more than one value is possible by passing a list.

```
In [125]: df00 = df.iloc[0, 0]

In [126]: df.replace([1.5, df00], [np.nan, "a"])
Out[126]:
          0         1
0         a -1.021415
1  0.432396  -0.32358
2  0.423825   0.79918
3  1.262614  0.751965
4       NaN       NaN
5       NaN       NaN
6 -0.498174 -1.060799
7  0.591667 -0.183257
8  1.019855 -1.482465
9       NaN       NaN

In [127]: df[1].dtype
Out[127]: dtype('float64')
```

You can also operate on the DataFrame in place:

```
In [128]: df.replace(1.5, np.nan, inplace=True)
```

Missing data casting rules and indexing

While pandas supports storing arrays of integer and boolean type, these types are not capable of storing missing data. Until we can switch to using a native NA type in NumPy, we've established some "casting rules". When a reindexing operation introduces missing data, the Series will be cast according to the rules introduced in the table below.

data type	Cast to
integer	float
boolean	object
float	no cast
object	no cast

For example:

```
In [129]: s = pd.Series(np.random.randn(5), index=[0, 2, 4, 6, 7])

In [130]: s > 0
Out[130]:
0     True
2     True
4     True
6     True
7     True
dtype: bool

In [131]: (s > 0).dtype
Out[131]: dtype('bool')

In [132]: crit = (s > 0).reindex(list(range(8)))

In [133]: crit
Out[133]:
0     True
1      NaN
2     True
3      NaN
4     True
5      NaN
6     True
7     True
dtype: object

In [134]: crit.dtype
Out[134]: dtype('O')
```

Ordinarily NumPy will complain if you try to use an object array (even if it contains boolean values) instead of a boolean array to get or set values from an ndarray (e.g. selecting values based on some criteria). If a boolean vector contains NAs, an exception will be generated:

```
In [135]: reindexed = s.reindex(list(range(8))).fillna(0)

In [136]: reindexed[crit]
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-136-0dac417a4890> in <module>
----> 1 reindexed[crit]
```

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```
/pandas/pandas/core/series.py in __getitem__(self, key)
    868             key = list(key)
    869
--> 870         if com.is_bool_indexer(key):
    871             key = check_bool_indexer(self.index, key)
    872             key = np.asarray(key, dtype=bool)

/pandas/pandas/core/common.py in is_bool_indexer(key)
    112                     # Don't raise on e.g. ["A", "B", np.nan], see
    113                     #  test_loc_getitem_list_of_labels_categoricalindex_with_
↪na
--> 114                     raise ValueError(na_msg)
    115                 return False
    116             return True

ValueError: Cannot mask with non-boolean array containing NA / NaN values
```

However, these can be filled in using *fillna()* and it will work fine:

```
In [137]: reindexed[crit.fillna(False)]
Out[137]:
0    0.126504
2    0.696198
4    0.697416
6    0.601516
7    0.003659
dtype: float64

In [138]: reindexed[crit.fillna(True)]
Out[138]:
0    0.126504
1    0.000000
2    0.696198
3    0.000000
4    0.697416
5    0.000000
6    0.601516
7    0.003659
dtype: float64
```

pandas provides a nullable integer dtype, but you must explicitly request it when creating the series or column. Notice that we use a capital "I" in the `dtype="Int64"`.

```
In [139]: s = pd.Series([0, 1, np.nan, 3, 4], dtype="Int64")

In [140]: s
Out[140]:
0       0
1       1
2    <NA>
3       3
4       4
dtype: Int64
```

See *Nullable integer data type* for more.

2.10.13 Experimental NA scalar to denote missing values

Warning: Experimental: the behaviour of pd.NA can still change without warning.

New in version 1.0.0.

Starting from pandas 1.0, an experimental pd.NA value (singleton) is available to represent scalar missing values. At this moment, it is used in the nullable *integer*, boolean and *dedicated string* data types as the missing value indicator.

The goal of pd.NA is provide a "missing" indicator that can be used consistently across data types (instead of np.nan, None or pd.NaT depending on the data type).

For example, when having missing values in a Series with the nullable integer dtype, it will use pd.NA:

```
In [141]: s = pd.Series([1, 2, None], dtype="Int64")

In [142]: s
Out[142]:
0       1
1       2
2    <NA>
dtype: Int64

In [143]: s[2]
Out[143]: <NA>

In [144]: s[2] is pd.NA
Out[144]: True
```

Currently, pandas does not yet use those data types by default (when creating a DataFrame or Series, or when reading in data), so you need to specify the dtype explicitly. An easy way to convert to those dtypes is explained *here*.

Propagation in arithmetic and comparison operations

In general, missing values *propagate* in operations involving pd.NA. When one of the operands is unknown, the outcome of the operation is also unknown.

For example, pd.NA propagates in arithmetic operations, similarly to np.nan:

```
In [145]: pd.NA + 1
Out[145]: <NA>

In [146]: "a" * pd.NA
Out[146]: <NA>
```

There are a few special cases when the result is known, even when one of the operands is NA.

```
In [147]: pd.NA ** 0
Out[147]: 1

In [148]: 1 ** pd.NA
Out[148]: 1
```

In equality and comparison operations, pd.NA also propagates. This deviates from the behaviour of np.nan, where comparisons with np.nan always return False.

```
In [149]: pd.NA == 1
Out[149]: <NA>

In [150]: pd.NA == pd.NA
Out[150]: <NA>

In [151]: pd.NA < 2.5
Out[151]: <NA>
```

To check if a value is equal to `pd.NA`, the *`isna()`* function can be used:

```
In [152]: pd.isna(pd.NA)
Out[152]: True
```

An exception on this basic propagation rule are *reductions* (such as the mean or the minimum), where pandas defaults to skipping missing values. See *above* for more.

Logical operations

For logical operations, `pd.NA` follows the rules of the three-valued logic (or *Kleene logic*, similarly to R, SQL and Julia). This logic means to only propagate missing values when it is logically required.

For example, for the logical "or" operation (`|`), if one of the operands is `True`, we already know the result will be `True`, regardless of the other value (so regardless the missing value would be `True` or `False`). In this case, `pd.NA` does not propagate:

```
In [153]: True | False
Out[153]: True

In [154]: True | pd.NA
Out[154]: True

In [155]: pd.NA | True
Out[155]: True
```

On the other hand, if one of the operands is `False`, the result depends on the value of the other operand. Therefore, in this case `pd.NA` propagates:

```
In [156]: False | True
Out[156]: True

In [157]: False | False
Out[157]: False

In [158]: False | pd.NA
Out[158]: <NA>
```

The behaviour of the logical "and" operation (`&`) can be derived using similar logic (where now `pd.NA` will not propagate if one of the operands is already `False`):

```
In [159]: False & True
Out[159]: False

In [160]: False & False
Out[160]: False
```

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```
In [161]: False & pd.NA
Out[161]: False
```

```
In [162]: True & True
Out[162]: True

In [163]: True & False
Out[163]: False

In [164]: True & pd.NA
Out[164]: <NA>
```

NA in a boolean context

Since the actual value of an NA is unknown, it is ambiguous to convert NA to a boolean value. The following raises an error:

```
In [165]: bool(pd.NA)
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-165-5477a57d5abb> in <module>
----> 1 bool(pd.NA)

/pandas/pandas/_libs/missing.pyx in pandas._libs.missing.NAType.__bool__()

TypeError: boolean value of NA is ambiguous
```

This also means that `pd.NA` cannot be used in a context where it is evaluated to a boolean, such as `if condition: ...` where `condition` can potentially be `pd.NA`. In such cases, *`isna()`* can be used to check for `pd.NA` or `condition` being `pd.NA` can be avoided, for example by filling missing values beforehand.

A similar situation occurs when using Series or DataFrame objects in `if` statements, see *Using if/truth statements with pandas*.

NumPy ufuncs

`pandas.NA` implements NumPy's `__array_ufunc__` protocol. Most ufuncs work with `NA`, and generally return `NA`:

```
In [166]: np.log(pd.NA)
Out[166]: <NA>

In [167]: np.add(pd.NA, 1)
Out[167]: <NA>
```

Warning: Currently, ufuncs involving an ndarray and `NA` will return an object-dtype filled with NA values.

```
In [168]: a = np.array([1, 2, 3])

In [169]: np.greater(a, pd.NA)
Out[169]: array([<NA>, <NA>, <NA>], dtype=object)
```

The return type here may change to return a different array type in the future.

See *DataFrame interoperability with NumPy functions* for more on ufuncs.

Conversion

If you have a DataFrame or Series using traditional types that have missing data represented using `np.nan`, there are convenience methods *convert_dtypes()* in Series and *convert_dtypes()* in DataFrame that can convert data to use the newer dtypes for integers, strings and booleans listed *here*. This is especially helpful after reading in data sets when letting the readers such as *read_csv()* and *read_excel()* infer default dtypes.

In this example, while the dtypes of all columns are changed, we show the results for the first 10 columns.

```
In [170]: bb = pd.read_csv("data/baseball.csv", index_col="id")

In [171]: bb[bb.columns[:10]].dtypes
Out[171]:
player    object
year       int64
stint      int64
team      object
lg        object
g          int64
ab         int64
r          int64
h          int64
X2b        int64
dtype: object
```

```
In [172]: bbn = bb.convert_dtypes()

In [173]: bbn[bbn.columns[:10]].dtypes
Out[173]:
player    string
year       Int64
stint      Int64
team      string
lg        string
g          Int64
ab         Int64
r          Int64
h          Int64
X2b        Int64
dtype: object
```

2.11 Duplicate Labels

`Index` objects are not required to be unique; you can have duplicate row or column labels. This may be a bit confusing at first. If you're familiar with SQL, you know that row labels are similar to a primary key on a table, and you would never want duplicates in a SQL table. But one of pandas' roles is to clean messy, real-world data before it goes to some downstream system. And real-world data has duplicates, even in fields that are supposed to be unique.

This section describes how duplicate labels change the behavior of certain operations, and how prevent duplicates from arising during operations, or to detect them if they do.

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

2.11.1 Consequences of Duplicate Labels

Some pandas methods (`Series.reindex()` for example) just don't work with duplicates present. The output can't be determined, and so pandas raises.

```
In [3]: s1 = pd.Series([0, 1, 2], index=["a", "b", "b"])

In [4]: s1.reindex(["a", "b", "c"])
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-4-18a38f6978fe> in <module>
----> 1 s1.reindex(["a", "b", "c"])

/pandas/pandas/core/series.py in reindex(self, index, **kwargs)
   4340     )
   4341     def reindex(self, index=None, **kwargs):
-> 4342         return super().reindex(index=index, **kwargs)
   4343
   4344     def drop(

/pandas/pandas/core/generic.py in reindex(self, *args, **kwargs)
   4806
   4807         # perform the reindex on the axes
-> 4808         return self._reindex_axes(
   4809             axes, level, limit, tolerance, method, fill_value, copy
   4810         ).__finalize__(self, method="reindex")

/pandas/pandas/core/generic.py in _reindex_axes(self, axes, level, limit, tolerance,␣
↪method, fill_value, copy)
   4827
   4828             axis = self._get_axis_number(a)
-> 4829             obj = obj._reindex_with_indexers(
   4830                 {axis: [new_index, indexer]},
   4831                 fill_value=fill_value,

/pandas/pandas/core/generic.py in _reindex_with_indexers(self, reindexers, fill_value,
↪ copy, allow_dups)
   4872
   4873             # TODO: speed up on homogeneous DataFrame objects
-> 4874             new_data = new_data.reindex_indexer(
   4875                 index,
   4876                 indexer,

/pandas/pandas/core/internals/managers.py in reindex_indexer(self, new_axis, indexer,␣
↪axis, fill_value, allow_dups, copy, consolidate, only_slice)
   1299         # some axes don't allow reindexing with dups
   1300         if not allow_dups:
-> 1301             self.axes[axis]._can_reindex(indexer)
   1302
   1303         if axis >= self.ndim:

/pandas/pandas/core/indexes/base.py in _can_reindex(self, indexer)
```

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```
   3474         # trying to reindex on an axis with duplicates
   3475         if not self._index_as_unique and len(indexer):
-> 3476             raise ValueError("cannot reindex from a duplicate axis")
   3477
   3478     def reindex(self, target, method=None, level=None, limit=None,␣
↪tolerance=None):

ValueError: cannot reindex from a duplicate axis
```

Other methods, like indexing, can give very surprising results. Typically indexing with a scalar will *reduce dimensionality*. Slicing a `DataFrame` with a scalar will return a `Series`. Slicing a `Series` with a scalar will return a scalar. But with duplicates, this isn't the case.

```
In [5]: df1 = pd.DataFrame([[0, 1, 2], [3, 4, 5]], columns=["A", "A", "B"])

In [6]: df1
Out[6]:
   A  A  B
0  0  1  2
1  3  4  5
```

We have duplicates in the columns. If we slice `'B'`, we get back a `Series`

```
In [7]: df1["B"]  # a series
Out[7]:
0    2
1    5
Name: B, dtype: int64
```

But slicing `'A'` returns a `DataFrame`

```
In [8]: df1["A"]  # a DataFrame
Out[8]:
   A  A
0  0  1
1  3  4
```

This applies to row labels as well

```
In [9]: df2 = pd.DataFrame({"A": [0, 1, 2]}, index=["a", "a", "b"])

In [10]: df2
Out[10]:
   A
a  0
a  1
b  2

In [11]: df2.loc["b", "A"]  # a scalar
Out[11]: 2

In [12]: df2.loc["a", "A"]  # a Series
Out[12]:
a    0
a    1
Name: A, dtype: int64
```

2.11.2 Duplicate Label Detection

You can check whether an `Index` (storing the row or column labels) is unique with `Index.is_unique`:

```
In [13]: df2
Out[13]:
   A
a  0
a  1
b  2

In [14]: df2.index.is_unique
Out[14]: False

In [15]: df2.columns.is_unique
Out[15]: True
```

Note: Checking whether an index is unique is somewhat expensive for large datasets. pandas does cache this result, so re-checking on the same index is very fast.

`Index.duplicated()` will return a boolean ndarray indicating whether a label is repeated.

```
In [16]: df2.index.duplicated()
Out[16]: array([False,  True, False])
```

Which can be used as a boolean filter to drop duplicate rows.

```
In [17]: df2.loc[~df2.index.duplicated(), :]
Out[17]:
   A
a  0
b  2
```

If you need additional logic to handle duplicate labels, rather than just dropping the repeats, using `groupby()` on the index is a common trick. For example, we'll resolve duplicates by taking the average of all rows with the same label.

```
In [18]: df2.groupby(level=0).mean()
Out[18]:
     A
a  0.5
b  2.0
```

2.11.3 Disallowing Duplicate Labels

New in version 1.2.0.

As noted above, handling duplicates is an important feature when reading in raw data. That said, you may want to avoid introducing duplicates as part of a data processing pipeline (from methods like *pandas.concat()*, `rename()`, etc.). Both `Series` and `DataFrame` *disallow* duplicate labels by calling `.set_flags(allows_duplicate_labels=False)`. (the default is to allow them). If there are duplicate labels, an exception will be raised.

```
In [19]: pd.Series([0, 1, 2], index=["a", "b", "b"]).set_flags(allows_duplicate_
↪labels=False)
---------------------------------------------------------------------------
DuplicateLabelError                       Traceback (most recent call last)
<ipython-input-19-11af4ee9738e> in <module>
----> 1 pd.Series([0, 1, 2], index=["a", "b", "b"]).set_flags(allows_duplicate_
↪labels=False)

/pandas/pandas/core/generic.py in set_flags(self, copy, allows_duplicate_labels)
    334         df = self.copy(deep=copy)
    335         if allows_duplicate_labels is not None:
--> 336             df.flags["allows_duplicate_labels"] = allows_duplicate_labels
    337         return df
    338

/pandas/pandas/core/flags.py in __setitem__(self, key, value)
    103         if key not in self._keys:
    104             raise ValueError(f"Unknown flag {key}. Must be one of {self._keys}
↪")
--> 105         setattr(self, key, value)
    106
    107     def __repr__(self):

/pandas/pandas/core/flags.py in allows_duplicate_labels(self, value)
     90         if not value:
     91             for ax in obj.axes:
---> 92                 ax._maybe_check_unique()
     93
     94         self._allows_duplicate_labels = value

/pandas/pandas/core/indexes/base.py in _maybe_check_unique(self)
    469             msg += f"\n{duplicates}"
    470
--> 471             raise DuplicateLabelError(msg)
    472
    473     @final

DuplicateLabelError: Index has duplicates.
      positions
label
b        [1, 2]
```

This applies to both row and column labels for a `DataFrame`

```
In [20]: pd.DataFrame([[0, 1, 2], [3, 4, 5]], columns=["A", "B", "C"],).set_flags(
   ....:     allows_duplicate_labels=False
   ....: )
   ....:
Out[20]:
   A  B  C
0  0  1  2
1  3  4  5
```

This attribute can be checked or set with `allows_duplicate_labels`, which indicates whether that object can have duplicate labels.

```
In [21]: df = pd.DataFrame({"A": [0, 1, 2, 3]}, index=["x", "y", "X", "Y"]).set_flags(
```

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```
   ....:     allows_duplicate_labels=False
   ....: )
   ....:

In [22]: df
Out[22]:
   A
x  0
y  1
X  2
Y  3

In [23]: df.flags.allows_duplicate_labels
Out[23]: False
```

`DataFrame.set_flags()` can be used to return a new `DataFrame` with attributes like `allows_duplicate_labels` set to some value

```
In [24]: df2 = df.set_flags(allows_duplicate_labels=True)

In [25]: df2.flags.allows_duplicate_labels
Out[25]: True
```

The new `DataFrame` returned is a view on the same data as the old `DataFrame`. Or the property can just be set directly on the same object

```
In [26]: df2.flags.allows_duplicate_labels = False

In [27]: df2.flags.allows_duplicate_labels
Out[27]: False
```

When processing raw, messy data you might initially read in the messy data (which potentially has duplicate labels), deduplicate, and then disallow duplicates going forward, to ensure that your data pipeline doesn't introduce duplicates.

```
>>> raw = pd.read_csv("...")
>>> deduplicated = raw.groupby(level=0).first()  # remove duplicates
>>> deduplicated.flags.allows_duplicate_labels = False  # disallow going forward
```

Setting `allows_duplicate_labels=True` on a `Series` or `DataFrame` with duplicate labels or performing an operation that introduces duplicate labels on a `Series` or `DataFrame` that disallows duplicates will raise an `errors.DuplicateLabelError`.

```
In [28]: df.rename(str.upper)
---------------------------------------------------------------------------
DuplicateLabelError                       Traceback (most recent call last)
<ipython-input-28-17c8fb0b7c7f> in <module>
----> 1 df.rename(str.upper)

/pandas/pandas/util/_decorators.py in wrapper(*args, **kwargs)
    310         @wraps(func)
    311         def wrapper(*args, **kwargs) -> Callable[..., Any]:
--> 312             return func(*args, **kwargs)
    313
    314         kind = inspect.Parameter.POSITIONAL_OR_KEYWORD

/pandas/pandas/core/frame.py in rename(self, mapper, index, columns, axis, copy,␣
↪inplace, level, errors)
```

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```
   4436         4  3  6
   4437         """
-> 4438         return super().rename(
   4439             mapper=mapper,
   4440             index=index,

/pandas/pandas/core/generic.py in rename(self, mapper, index, columns, axis, copy,␣
↪inplace, level, errors)
   1062             return None
   1063         else:
-> 1064             return result.__finalize__(self, method="rename")
   1065
   1066     @rewrite_axis_style_signature("mapper", [("copy", True), ("inplace",␣
↪False)])

/pandas/pandas/core/generic.py in __finalize__(self, other, method, **kwargs)
   5430                 self.attrs[name] = other.attrs[name]
   5431
-> 5432             self.flags.allows_duplicate_labels = other.flags.allows_duplicate_
↪labels
   5433             # For subclasses using _metadata.
   5434             for name in set(self._metadata) & set(other._metadata):

/pandas/pandas/core/flags.py in allows_duplicate_labels(self, value)
     90         if not value:
     91             for ax in obj.axes:
---> 92                 ax._maybe_check_unique()
     93
     94         self._allows_duplicate_labels = value

/pandas/pandas/core/indexes/base.py in _maybe_check_unique(self)
    469             msg += f"\n{duplicates}"
    470
--> 471             raise DuplicateLabelError(msg)
    472
    473     @final

DuplicateLabelError: Index has duplicates.
      positions
label
X        [0, 2]
Y        [1, 3]
```

This error message contains the labels that are duplicated, and the numeric positions of all the duplicates (including the "original") in the `Series` or `DataFrame`

Duplicate Label Propagation

In general, disallowing duplicates is "sticky". It's preserved through operations.

```
In [29]: s1 = pd.Series(0, index=["a", "b"]).set_flags(allows_duplicate_labels=False)

In [30]: s1
Out[30]:
a    0
b    0
dtype: int64

In [31]: s1.head().rename({"a": "b"})
---------------------------------------------------------------------------
DuplicateLabelError                       Traceback (most recent call last)
<ipython-input-31-8f09bda3af1a> in <module>
----> 1 s1.head().rename({"a": "b"})

/pandas/pandas/core/series.py in rename(self, index, axis, copy, inplace, level,␣
↪errors)
   4298         """
   4299         if callable(index) or is_dict_like(index):
-> 4300             return super().rename(
   4301                 index, copy=copy, inplace=inplace, level=level, errors=errors
   4302             )

/pandas/pandas/core/generic.py in rename(self, mapper, index, columns, axis, copy,␣
↪inplace, level, errors)
   1062             return None
   1063         else:
-> 1064             return result.__finalize__(self, method="rename")
   1065
   1066     @rewrite_axis_style_signature("mapper", [("copy", True), ("inplace",␣
↪False)])

/pandas/pandas/core/generic.py in __finalize__(self, other, method, **kwargs)
   5430                 self.attrs[name] = other.attrs[name]
   5431
-> 5432             self.flags.allows_duplicate_labels = other.flags.allows_duplicate_
↪labels
   5433             # For subclasses using _metadata.
   5434             for name in set(self._metadata) & set(other._metadata):

/pandas/pandas/core/flags.py in allows_duplicate_labels(self, value)
     90         if not value:
     91             for ax in obj.axes:
---> 92                 ax._maybe_check_unique()
     93
     94         self._allows_duplicate_labels = value

/pandas/pandas/core/indexes/base.py in _maybe_check_unique(self)
    469             msg += f"\n{duplicates}"
    470
--> 471             raise DuplicateLabelError(msg)
    472
    473     @final

DuplicateLabelError: Index has duplicates.
```

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```
      positions
label
b         [0, 1]
```

Warning: This is an experimental feature. Currently, many methods fail to propagate the `allows_duplicate_labels` value. In future versions it is expected that every method taking or returning one or more DataFrame or Series objects will propagate `allows_duplicate_labels`.

2.12 Categorical data

This is an introduction to pandas categorical data type, including a short comparison with R's `factor`.

`Categoricals` are a pandas data type corresponding to categorical variables in statistics. A categorical variable takes on a limited, and usually fixed, number of possible values (`categories`; `levels` in R). Examples are gender, social class, blood type, country affiliation, observation time or rating via Likert scales.

In contrast to statistical categorical variables, categorical data might have an order (e.g. 'strongly agree' vs 'agree' or 'first observation' vs. 'second observation'), but numerical operations (additions, divisions, ...) are not possible.

All values of categorical data are either in `categories` or `np.nan`. Order is defined by the order of `categories`, not lexical order of the values. Internally, the data structure consists of a `categories` array and an integer array of `codes` which point to the real value in the `categories` array.

The categorical data type is useful in the following cases:

- A string variable consisting of only a few different values. Converting such a string variable to a categorical variable will save some memory, see *here*.
- The lexical order of a variable is not the same as the logical order ("one", "two", "three"). By converting to a categorical and specifying an order on the categories, sorting and min/max will use the logical order instead of the lexical order, see *here*.
- As a signal to other Python libraries that this column should be treated as a categorical variable (e.g. to use suitable statistical methods or plot types).

See also the *API docs on categoricals*.

2.12.1 Object creation

Series creation

Categorical `Series` or columns in a `DataFrame` can be created in several ways:

By specifying `dtype="category"` when constructing a `Series`:

```
In [1]: s = pd.Series(["a", "b", "c", "a"], dtype="category")

In [2]: s
Out[2]:
0    a
1    b
2    c
3    a
```

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```
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

By converting an existing `Series` or column to a `category` dtype:

```
In [3]: df = pd.DataFrame({"A": ["a", "b", "c", "a"]})

In [4]: df["B"] = df["A"].astype("category")

In [5]: df
Out[5]:
   A  B
0  a  a
1  b  b
2  c  c
3  a  a
```

By using special functions, such as *`cut()`*, which groups data into discrete bins. See the *example on tiling* in the docs.

```
In [6]: df = pd.DataFrame({"value": np.random.randint(0, 100, 20)})

In [7]: labels = ["{0} - {1}".format(i, i + 9) for i in range(0, 100, 10)]

In [8]: df["group"] = pd.cut(df.value, range(0, 105, 10), right=False, labels=labels)

In [9]: df.head(10)
Out[9]:
   value    group
0     65  60 - 69
1     49  40 - 49
2     56  50 - 59
3     43  40 - 49
4     43  40 - 49
5     91  90 - 99
6     32  30 - 39
7     87  80 - 89
8     36  30 - 39
9      8    0 - 9
```

By passing a *`pandas.Categorical`* object to a `Series` or assigning it to a `DataFrame`.

```
In [10]: raw_cat = pd.Categorical(
   ....:     ["a", "b", "c", "a"], categories=["b", "c", "d"], ordered=False
   ....: )
   ....:

In [11]: s = pd.Series(raw_cat)

In [12]: s
Out[12]:
0    NaN
1      b
2      c
3    NaN
dtype: category
```

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```
Categories (3, object): ['b', 'c', 'd']

In [13]: df = pd.DataFrame({"A": ["a", "b", "c", "a"]})

In [14]: df["B"] = raw_cat

In [15]: df
Out[15]:
   A    B
0  a  NaN
1  b    b
2  c    c
3  a  NaN
```

Categorical data has a specific `category` *dtype*:

```
In [16]: df.dtypes
Out[16]:
A       object
B    category
dtype: object
```

DataFrame creation

Similar to the previous section where a single column was converted to categorical, all columns in a `DataFrame` can be batch converted to categorical either during or after construction.

This can be done during construction by specifying `dtype="category"` in the `DataFrame` constructor:

```
In [17]: df = pd.DataFrame({"A": list("abca"), "B": list("bccd")}, dtype="category")

In [18]: df.dtypes
Out[18]:
A    category
B    category
dtype: object
```

Note that the categories present in each column differ; the conversion is done column by column, so only labels present in a given column are categories:

```
In [19]: df["A"]
Out[19]:
0    a
1    b
2    c
3    a
Name: A, dtype: category
Categories (3, object): ['a', 'b', 'c']

In [20]: df["B"]
Out[20]:
0    b
1    c
2    c
3    d
```

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```
Name: B, dtype: category
Categories (3, object): ['b', 'c', 'd']
```

Analogously, all columns in an existing `DataFrame` can be batch converted using *DataFrame.astype()*:

```
In [21]: df = pd.DataFrame({"A": list("abca"), "B": list("bccd")})

In [22]: df_cat = df.astype("category")

In [23]: df_cat.dtypes
Out[23]:
A    category
B    category
dtype: object
```

This conversion is likewise done column by column:

```
In [24]: df_cat["A"]
Out[24]:
0    a
1    b
2    c
3    a
Name: A, dtype: category
Categories (3, object): ['a', 'b', 'c']

In [25]: df_cat["B"]
Out[25]:
0    b
1    c
2    c
3    d
Name: B, dtype: category
Categories (3, object): ['b', 'c', 'd']
```

Controlling behavior

In the examples above where we passed `dtype='category'`, we used the default behavior:

1. Categories are inferred from the data.
2. Categories are unordered.

To control those behaviors, instead of passing `'category'`, use an instance of `CategoricalDtype`.

```
In [26]: from pandas.api.types import CategoricalDtype

In [27]: s = pd.Series(["a", "b", "c", "a"])

In [28]: cat_type = CategoricalDtype(categories=["b", "c", "d"], ordered=True)

In [29]: s_cat = s.astype(cat_type)

In [30]: s_cat
Out[30]:
0    NaN
```

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```
1      b
2      c
3    NaN
dtype: category
Categories (3, object): ['b' < 'c' < 'd']
```

Similarly, a `CategoricalDtype` can be used with a `DataFrame` to ensure that categories are consistent among all columns.

```
In [31]: from pandas.api.types import CategoricalDtype

In [32]: df = pd.DataFrame({"A": list("abca"), "B": list("bccd")})

In [33]: cat_type = CategoricalDtype(categories=list("abcd"), ordered=True)

In [34]: df_cat = df.astype(cat_type)

In [35]: df_cat["A"]
Out[35]:
0    a
1    b
2    c
3    a
Name: A, dtype: category
Categories (4, object): ['a' < 'b' < 'c' < 'd']

In [36]: df_cat["B"]
Out[36]:
0    b
1    c
2    c
3    d
Name: B, dtype: category
Categories (4, object): ['a' < 'b' < 'c' < 'd']
```

Note: To perform table-wise conversion, where all labels in the entire `DataFrame` are used as categories for each column, the `categories` parameter can be determined programmatically by `categories = pd.unique(df.to_numpy().ravel())`.

If you already have `codes` and `categories`, you can use the *`from_codes()`* constructor to save the factorize step during normal constructor mode:

```
In [37]: splitter = np.random.choice([0, 1], 5, p=[0.5, 0.5])

In [38]: s = pd.Series(pd.Categorical.from_codes(splitter, categories=["train", "test
↪"]))
```

Regaining original data

To get back to the original `Series` or NumPy array, use `Series.astype(original_dtype)` or `np.asarray(categorical)`:

```
In [39]: s = pd.Series(["a", "b", "c", "a"])

In [40]: s
Out[40]:
0    a
1    b
2    c
3    a
dtype: object

In [41]: s2 = s.astype("category")

In [42]: s2
Out[42]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): ['a', 'b', 'c']

In [43]: s2.astype(str)
Out[43]:
0    a
1    b
2    c
3    a
dtype: object

In [44]: np.asarray(s2)
Out[44]: array(['a', 'b', 'c', 'a'], dtype=object)
```

Note: In contrast to R's `factor` function, categorical data is not converting input values to strings; categories will end up the same data type as the original values.

Note: In contrast to R's `factor` function, there is currently no way to assign/change labels at creation time. Use `categories` to change the categories after creation time.

2.12.2 CategoricalDtype

A categorical's type is fully described by

1. `categories`: a sequence of unique values and no missing values
2. `ordered`: a boolean

This information can be stored in a `CategoricalDtype`. The `categories` argument is optional, which implies that the actual categories should be inferred from whatever is present in the data when the *pandas.Categorical* is created. The categories are assumed to be unordered by default.

```
In [45]: from pandas.api.types import CategoricalDtype

In [46]: CategoricalDtype(["a", "b", "c"])
Out[46]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=False)

In [47]: CategoricalDtype(["a", "b", "c"], ordered=True)
Out[47]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=True)

In [48]: CategoricalDtype()
Out[48]: CategoricalDtype(categories=None, ordered=False)
```

A `CategoricalDtype` can be used in any place pandas expects a `dtype`. For example *pandas.read_csv()*, *pandas.DataFrame.astype()*, or in the `Series` constructor.

Note: As a convenience, you can use the string `'category'` in place of a `CategoricalDtype` when you want the default behavior of the categories being unordered, and equal to the set values present in the array. In other words, `dtype='category'` is equivalent to `dtype=CategoricalDtype()`.

Equality semantics

Two instances of `CategoricalDtype` compare equal whenever they have the same categories and order. When comparing two unordered categoricals, the order of the `categories` is not considered.

```
In [49]: c1 = CategoricalDtype(["a", "b", "c"], ordered=False)

# Equal, since order is not considered when ordered=False
In [50]: c1 == CategoricalDtype(["b", "c", "a"], ordered=False)
Out[50]: True

# Unequal, since the second CategoricalDtype is ordered
In [51]: c1 == CategoricalDtype(["a", "b", "c"], ordered=True)
Out[51]: False
```

All instances of `CategoricalDtype` compare equal to the string `'category'`.

```
In [52]: c1 == "category"
Out[52]: True
```

Warning: Since `dtype='category'` is essentially `CategoricalDtype(None, False)`, and since all instances `CategoricalDtype` compare equal to `'category'`, all instances of `CategoricalDtype` compare equal to a `CategoricalDtype(None, False)`, regardless of `categories` or `ordered`.

2.12.3 Description

Using *describe()* on categorical data will produce similar output to a `Series` or `DataFrame` of type `string`.

```
In [53]: cat = pd.Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c"])

In [54]: df = pd.DataFrame({"cat": cat, "s": ["a", "c", "c", np.nan]})

In [55]: df.describe()
Out[55]:
       cat  s
count    3  3
unique   2  2
top      c  c
freq     2  2

In [56]: df["cat"].describe()
Out[56]:
count     3
unique    2
top       c
freq      2
Name: cat, dtype: object
```

2.12.4 Working with categories

Categorical data has a `categories` and a `ordered` property, which list their possible values and whether the ordering matters or not. These properties are exposed as `s.cat.categories` and `s.cat.ordered`. If you don't manually specify categories and ordering, they are inferred from the passed arguments.

```
In [57]: s = pd.Series(["a", "b", "c", "a"], dtype="category")

In [58]: s.cat.categories
Out[58]: Index(['a', 'b', 'c'], dtype='object')

In [59]: s.cat.ordered
Out[59]: False
```

It's also possible to pass in the categories in a specific order:

```
In [60]: s = pd.Series(pd.Categorical(["a", "b", "c", "a"], categories=["c", "b", "a
↪"]))

In [61]: s.cat.categories
Out[61]: Index(['c', 'b', 'a'], dtype='object')

In [62]: s.cat.ordered
Out[62]: False
```

Note: New categorical data are **not** automatically ordered. You must explicitly pass `ordered=True` to indicate an ordered `Categorical`.

Note: The result of *unique()* is not always the same as `Series.cat.categories`, because `Series.unique()` has a couple of guarantees, namely that it returns categories in the order of appearance, and it only

includes values that are actually present.

```
In [63]: s = pd.Series(list("babc")).astype(CategoricalDtype(list("abcd")))

In [64]: s
Out[64]:
0    b
1    a
2    b
3    c
dtype: category
Categories (4, object): ['a', 'b', 'c', 'd']

# categories
In [65]: s.cat.categories
Out[65]: Index(['a', 'b', 'c', 'd'], dtype='object')

# uniques
In [66]: s.unique()
Out[66]:
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```

Renaming categories

Renaming categories is done by assigning new values to the `Series.cat.categories` property or by using the `rename_categories()` method:

```
In [67]: s = pd.Series(["a", "b", "c", "a"], dtype="category")

In [68]: s
Out[68]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): ['a', 'b', 'c']

In [69]: s.cat.categories = ["Group %s" % g for g in s.cat.categories]

In [70]: s
Out[70]:
0    Group a
1    Group b
2    Group c
3    Group a
dtype: category
Categories (3, object): ['Group a', 'Group b', 'Group c']

In [71]: s = s.cat.rename_categories([1, 2, 3])

In [72]: s
Out[72]:
0    1
```

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```
1    2
2    3
3    1
dtype: category
Categories (3, int64): [1, 2, 3]

# You can also pass a dict-like object to map the renaming
In [73]: s = s.cat.rename_categories({1: "x", 2: "y", 3: "z"})

In [74]: s
Out[74]:
0    x
1    y
2    z
3    x
dtype: category
Categories (3, object): ['x', 'y', 'z']
```

Note: In contrast to R's `factor`, categorical data can have categories of other types than string.

Note: Be aware that assigning new categories is an inplace operation, while most other operations under `Series.cat` per default return a new `Series` of dtype `category`.

Categories must be unique or a `ValueError` is raised:

```
In [75]: try:
   ....:     s.cat.categories = [1, 1, 1]
   ....: except ValueError as e:
   ....:     print("ValueError:", str(e))
   ....:
ValueError: Categorical categories must be unique
```

Categories must also not be `NaN` or a `ValueError` is raised:

```
In [76]: try:
   ....:     s.cat.categories = [1, 2, np.nan]
   ....: except ValueError as e:
   ....:     print("ValueError:", str(e))
   ....:
ValueError: Categorical categories cannot be null
```

Appending new categories

Appending categories can be done by using the `add_categories()` method:

```
In [77]: s = s.cat.add_categories([4])

In [78]: s.cat.categories
Out[78]: Index(['x', 'y', 'z', 4], dtype='object')

In [79]: s
```

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```
Out[79]:
0    x
1    y
2    z
3    x
dtype: category
Categories (4, object): ['x', 'y', 'z', 4]
```

Removing categories

Removing categories can be done by using the `remove_categories()` method. Values which are removed are replaced by `np.nan`.:

```
In [80]: s = s.cat.remove_categories([4])

In [81]: s
Out[81]:
0    x
1    y
2    z
3    x
dtype: category
Categories (3, object): ['x', 'y', 'z']
```

Removing unused categories

Removing unused categories can also be done:

```
In [82]: s = pd.Series(pd.Categorical(["a", "b", "a"], categories=["a", "b", "c", "d
↪"]))

In [83]: s
Out[83]:
0    a
1    b
2    a
dtype: category
Categories (4, object): ['a', 'b', 'c', 'd']

In [84]: s.cat.remove_unused_categories()
Out[84]:
0    a
1    b
2    a
dtype: category
Categories (2, object): ['a', 'b']
```

Setting categories

If you want to do remove and add new categories in one step (which has some speed advantage), or simply set the categories to a predefined scale, use `set_categories()`.

```
In [85]: s = pd.Series(["one", "two", "four", "-"], dtype="category")

In [86]: s
Out[86]:
0     one
1     two
2    four
3       -
dtype: category
Categories (4, object): ['-', 'four', 'one', 'two']

In [87]: s = s.cat.set_categories(["one", "two", "three", "four"])

In [88]: s
Out[88]:
0     one
1     two
2    four
3     NaN
dtype: category
Categories (4, object): ['one', 'two', 'three', 'four']
```

Note: Be aware that `Categorical.set_categories()` cannot know whether some category is omitted intentionally or because it is misspelled or (under Python3) due to a type difference (e.g., NumPy S1 dtype and Python strings). This can result in surprising behaviour!

2.12.5 Sorting and order

If categorical data is ordered (`s.cat.ordered == True`), then the order of the categories has a meaning and certain operations are possible. If the categorical is unordered, `.min()/.max()` will raise a `TypeError`.

```
In [89]: s = pd.Series(pd.Categorical(["a", "b", "c", "a"], ordered=False))

In [90]: s.sort_values(inplace=True)

In [91]: s = pd.Series(["a", "b", "c", "a"]).astype(CategoricalDtype(ordered=True))

In [92]: s.sort_values(inplace=True)

In [93]: s
Out[93]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): ['a' < 'b' < 'c']
```

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```
In [94]: s.min(), s.max()
Out[94]: ('a', 'c')
```

You can set categorical data to be ordered by using `as_ordered()` or unordered by using `as_unordered()`. These will by default return a *new* object.

```
In [95]: s.cat.as_ordered()
Out[95]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): ['a' < 'b' < 'c']

In [96]: s.cat.as_unordered()
Out[96]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

Sorting will use the order defined by categories, not any lexical order present on the data type. This is even true for strings and numeric data:

```
In [97]: s = pd.Series([1, 2, 3, 1], dtype="category")

In [98]: s = s.cat.set_categories([2, 3, 1], ordered=True)

In [99]: s
Out[99]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [100]: s.sort_values(inplace=True)

In [101]: s
Out[101]:
1    2
2    3
0    1
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [102]: s.min(), s.max()
Out[102]: (2, 1)
```

Reordering

Reordering the categories is possible via the `Categorical.reorder_categories()` and the `Categorical.set_categories()` methods. For `Categorical.reorder_categories()`, all old categories must be included in the new categories and no new categories are allowed. This will necessarily make the sort order the same as the categories order.

```
In [103]: s = pd.Series([1, 2, 3, 1], dtype="category")

In [104]: s = s.cat.reorder_categories([2, 3, 1], ordered=True)

In [105]: s
Out[105]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [106]: s.sort_values(inplace=True)

In [107]: s
Out[107]:
1    2
2    3
0    1
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [108]: s.min(), s.max()
Out[108]: (2, 1)
```

Note: Note the difference between assigning new categories and reordering the categories: the first renames categories and therefore the individual values in the `Series`, but if the first position was sorted last, the renamed value will still be sorted last. Reordering means that the way values are sorted is different afterwards, but not that individual values in the `Series` are changed.

Note: If the `Categorical` is not ordered, *`Series.min()`* and *`Series.max()`* will raise `TypeError`. Numeric operations like `+`, `-`, `*`, `/` and operations based on them (e.g. *`Series.median()`*, which would need to compute the mean between two values if the length of an array is even) do not work and raise a `TypeError`.

Multi column sorting

A categorical dtyped column will participate in a multi-column sort in a similar manner to other columns. The ordering of the categorical is determined by the `categories` of that column.

```
In [109]: dfs = pd.DataFrame(
   .....:     {
   .....:         "A": pd.Categorical(
   .....:             list("bbeebbaa"),
   .....:             categories=["e", "a", "b"],
   .....:             ordered=True,
   .....:         ),
   .....:         "B": [1, 2, 1, 2, 2, 1, 2, 1],
   .....:     }
   .....: )
   .....:

In [110]: dfs.sort_values(by=["A", "B"])
Out[110]:
   A  B
2  e  1
3  e  2
7  a  1
6  a  2
0  b  1
5  b  1
1  b  2
4  b  2
```

Reordering the `categories` changes a future sort.

```
In [111]: dfs["A"] = dfs["A"].cat.reorder_categories(["a", "b", "e"])

In [112]: dfs.sort_values(by=["A", "B"])
Out[112]:
   A  B
7  a  1
6  a  2
0  b  1
5  b  1
1  b  2
4  b  2
2  e  1
3  e  2
```

2.12.6 Comparisons

Comparing categorical data with other objects is possible in three cases:

- Comparing equality (== and !=) to a list-like object (list, Series, array, ...) of the same length as the categorical data.
- All comparisons (==, !=, >, >=, <, and <=) of categorical data to another categorical Series, when `ordered==True` and the `categories` are the same.
- All comparisons of a categorical data to a scalar.

All other comparisons, especially "non-equality" comparisons of two categoricals with different categories or a categorical with any list-like object, will raise a `TypeError`.

Note: Any "non-equality" comparisons of categorical data with a `Series`, `np.array`, `list` or categorical data with different categories or ordering will raise a `TypeError` because custom categories ordering could be interpreted in two ways: one with taking into account the ordering and one without.

```
In [113]: cat = pd.Series([1, 2, 3]).astype(CategoricalDtype([3, 2, 1], ordered=True))

In [114]: cat_base = pd.Series([2, 2, 2]).astype(CategoricalDtype([3, 2, 1],␣
↪ordered=True))

In [115]: cat_base2 = pd.Series([2, 2, 2]).astype(CategoricalDtype(ordered=True))

In [116]: cat
Out[116]:
0    1
1    2
2    3
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [117]: cat_base
Out[117]:
0    2
1    2
2    2
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [118]: cat_base2
Out[118]:
0    2
1    2
2    2
dtype: category
Categories (1, int64): [2]
```

Comparing to a categorical with the same categories and ordering or to a scalar works:

```
In [119]: cat > cat_base
Out[119]:
0     True
1    False
2    False
dtype: bool

In [120]: cat > 2
Out[120]:
0     True
1    False
2    False
dtype: bool
```

Equality comparisons work with any list-like object of same length and scalars:

```
In [121]: cat == cat_base
Out[121]:
0    False
1     True
2    False
dtype: bool

In [122]: cat == np.array([1, 2, 3])
Out[122]:
0    True
1    True
2    True
dtype: bool

In [123]: cat == 2
Out[123]:
0    False
1     True
2    False
dtype: bool
```

This doesn't work because the categories are not the same:

```
In [124]: try:
   .....:     cat > cat_base2
   .....: except TypeError as e:
   .....:     print("TypeError:", str(e))
   .....:
TypeError: Categoricals can only be compared if 'categories' are the same.
```

If you want to do a "non-equality" comparison of a categorical series with a list-like object which is not categorical data, you need to be explicit and convert the categorical data back to the original values:

```
In [125]: base = np.array([1, 2, 3])

In [126]: try:
   .....:     cat > base
   .....: except TypeError as e:
   .....:     print("TypeError:", str(e))
   .....:
TypeError: Cannot compare a Categorical for op __gt__ with type <class 'numpy.ndarray
↪'>.
If you want to compare values, use 'np.asarray(cat) <op> other'.

In [127]: np.asarray(cat) > base
Out[127]: array([False, False, False])
```

When you compare two unordered categoricals with the same categories, the order is not considered:

```
In [128]: c1 = pd.Categorical(["a", "b"], categories=["a", "b"], ordered=False)

In [129]: c2 = pd.Categorical(["a", "b"], categories=["b", "a"], ordered=False)

In [130]: c1 == c2
Out[130]: array([ True,  True])
```

2.12.7 Operations

Apart from *Series.min()*, *Series.max()* and *Series.mode()*, the following operations are possible with categorical data:

`Series` methods like *Series.value_counts()* will use all categories, even if some categories are not present in the data:

```
In [131]: s = pd.Series(pd.Categorical(["a", "b", "c", "c"], categories=["c", "a", "b
↪", "d"]))

In [132]: s.value_counts()
Out[132]:
c    2
a    1
b    1
d    0
dtype: int64
```

`DataFrame` methods like *DataFrame.sum()* also show "unused" categories.

```
In [133]: columns = pd.Categorical(
   .....:     ["One", "One", "Two"], categories=["One", "Two", "Three"], ordered=True
   .....: )
   .....:

In [134]: df = pd.DataFrame(
   .....:     data=[[1, 2, 3], [4, 5, 6]],
   .....:     columns=pd.MultiIndex.from_arrays([["A", "B", "B"], columns]),
   .....: )
   .....:

In [135]: df.sum(axis=1, level=1)
Out[135]:
   One  Two  Three
0    3    3      0
1    9    6      0
```

Groupby will also show "unused" categories:

```
In [136]: cats = pd.Categorical(
   .....:     ["a", "b", "b", "b", "c", "c", "c"], categories=["a", "b", "c", "d"]
   .....: )
   .....:

In [137]: df = pd.DataFrame({"cats": cats, "values": [1, 2, 2, 2, 3, 4, 5]})

In [138]: df.groupby("cats").mean()
Out[138]:
      values
cats
a        1.0
b        2.0
c        4.0
d        NaN

In [139]: cats2 = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])
```

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```
In [140]: df2 = pd.DataFrame(
   .....:     {
   .....:         "cats": cats2,
   .....:         "B": ["c", "d", "c", "d"],
   .....:         "values": [1, 2, 3, 4],
   .....:     }
   .....: )
   .....:

In [141]: df2.groupby(["cats", "B"]).mean()
Out[141]:
        values
cats B
a    c     1.0
     d     2.0
b    c     3.0
     d     4.0
c    c     NaN
     d     NaN
```

Pivot tables:

```
In [142]: raw_cat = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])

In [143]: df = pd.DataFrame({"A": raw_cat, "B": ["c", "d", "c", "d"], "values": [1, 2,
↪ 3, 4]})

In [144]: pd.pivot_table(df, values="values", index=["A", "B"])
Out[144]:
     values
A B
a c       1
  d       2
b c       3
  d       4
```

2.12.8 Data munging

The optimized pandas data access methods `.loc`, `.iloc`, `.at`, and `.iat`, work as normal. The only difference is the return type (for getting) and that only values already in `categories` can be assigned.

Getting

If the slicing operation returns either a `DataFrame` or a column of type `Series`, the `category` dtype is preserved.

```
In [145]: idx = pd.Index(["h", "i", "j", "k", "l", "m", "n"])

In [146]: cats = pd.Series(["a", "b", "b", "b", "c", "c", "c"], dtype="category",␣
↪index=idx)

In [147]: values = [1, 2, 2, 2, 3, 4, 5]

In [148]: df = pd.DataFrame({"cats": cats, "values": values}, index=idx)
```

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```
In [149]: df.iloc[2:4, :]
Out[149]:
  cats  values
j    b       2
k    b       2

In [150]: df.iloc[2:4, :].dtypes
Out[150]:
cats      category
values       int64
dtype: object

In [151]: df.loc["h":"j", "cats"]
Out[151]:
h    a
i    b
j    b
Name: cats, dtype: category
Categories (3, object): ['a', 'b', 'c']

In [152]: df[df["cats"] == "b"]
Out[152]:
  cats  values
i    b       2
j    b       2
k    b       2
```

An example where the category type is not preserved is if you take one single row: the resulting `Series` is of dtype `object`:

```
# get the complete "h" row as a Series
In [153]: df.loc["h", :]
Out[153]:
cats      a
values    1
Name: h, dtype: object
```

Returning a single item from categorical data will also return the value, not a categorical of length "1".

```
In [154]: df.iat[0, 0]
Out[154]: 'a'

In [155]: df["cats"].cat.categories = ["x", "y", "z"]

In [156]: df.at["h", "cats"]  # returns a string
Out[156]: 'x'
```

Note: The is in contrast to R's `factor` function, where `factor(c(1,2,3))[1]` returns a single value `factor`.

To get a single value `Series` of type `category`, you pass in a list with a single value:

```
In [157]: df.loc[["h"], "cats"]
Out[157]:
h    x
```

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```
Name: cats, dtype: category
Categories (3, object): ['x', 'y', 'z']
```

String and datetime accessors

The accessors `.dt` and `.str` will work if the `s.cat.categories` are of an appropriate type:

```
In [158]: str_s = pd.Series(list("aabb"))

In [159]: str_cat = str_s.astype("category")

In [160]: str_cat
Out[160]:
0    a
1    a
2    b
3    b
dtype: category
Categories (2, object): ['a', 'b']

In [161]: str_cat.str.contains("a")
Out[161]:
0     True
1     True
2    False
3    False
dtype: bool

In [162]: date_s = pd.Series(pd.date_range("1/1/2015", periods=5))

In [163]: date_cat = date_s.astype("category")

In [164]: date_cat
Out[164]:
0   2015-01-01
1   2015-01-02
2   2015-01-03
3   2015-01-04
4   2015-01-05
dtype: category
Categories (5, datetime64[ns]): [2015-01-01, 2015-01-02, 2015-01-03, 2015-01-04, 2015-
↪01-05]

In [165]: date_cat.dt.day
Out[165]:
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

Note: The returned `Series` (or `DataFrame`) is of the same type as if you used the `.str.<method>` / `.dt.<method>` on a `Series` of that type (and not of type `category`!).

That means, that the returned values from methods and properties on the accessors of a `Series` and the returned values from methods and properties on the accessors of this `Series` transformed to one of type `category` will be equal:

```
In [166]: ret_s = str_s.str.contains("a")

In [167]: ret_cat = str_cat.str.contains("a")

In [168]: ret_s.dtype == ret_cat.dtype
Out[168]: True

In [169]: ret_s == ret_cat
Out[169]:
0    True
1    True
2    True
3    True
dtype: bool
```

Note: The work is done on the `categories` and then a new `Series` is constructed. This has some performance implication if you have a `Series` of type string, where lots of elements are repeated (i.e. the number of unique elements in the `Series` is a lot smaller than the length of the `Series`). In this case it can be faster to convert the original `Series` to one of type `category` and use `.str.<method>` or `.dt.<property>` on that.

Setting

Setting values in a categorical column (or `Series`) works as long as the value is included in the `categories`:

```
In [170]: idx = pd.Index(["h", "i", "j", "k", "l", "m", "n"])

In [171]: cats = pd.Categorical(["a", "a", "a", "a", "a", "a", "a"], categories=["a",
↪"b"])

In [172]: values = [1, 1, 1, 1, 1, 1, 1]

In [173]: df = pd.DataFrame({"cats": cats, "values": values}, index=idx)

In [174]: df.iloc[2:4, :] = [["b", 2], ["b", 2]]

In [175]: df
Out[175]:
  cats  values
h    a       1
i    a       1
j    b       2
k    b       2
l    a       1
m    a       1
n    a       1

In [176]: try:
   .....:     df.iloc[2:4, :] = [["c", 3], ["c", 3]]
   .....: except ValueError as e:
   .....:     print("ValueError:", str(e))
```

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```
   .....:
ValueError: Cannot setitem on a Categorical with a new category, set the categories␣
↪first
```

Setting values by assigning categorical data will also check that the `categories` match:

```
In [177]: df.loc["j":"k", "cats"] = pd.Categorical(["a", "a"], categories=["a", "b"])

In [178]: df
Out[178]:
  cats  values
h    a       1
i    a       1
j    a       2
k    a       2
l    a       1
m    a       1
n    a       1

In [179]: try:
   .....:     df.loc["j":"k", "cats"] = pd.Categorical(["b", "b"], categories=["a", "b
↪", "c"])
   .....: except ValueError as e:
   .....:     print("ValueError:", str(e))
   .....:
ValueError: Cannot set a Categorical with another, without identical categories
```

Assigning a `Categorical` to parts of a column of other types will use the values:

```
In [180]: df = pd.DataFrame({"a": [1, 1, 1, 1, 1], "b": ["a", "a", "a", "a", "a"]})

In [181]: df.loc[1:2, "a"] = pd.Categorical(["b", "b"], categories=["a", "b"])

In [182]: df.loc[2:3, "b"] = pd.Categorical(["b", "b"], categories=["a", "b"])

In [183]: df
Out[183]:
   a  b
0  1  a
1  b  a
2  b  b
3  1  b
4  1  a

In [184]: df.dtypes
Out[184]:
a    object
b    object
dtype: object
```

Merging / concatenation

By default, combining `Series` or `DataFrames` which contain the same categories results in `category` dtype, otherwise results will depend on the dtype of the underlying categories. Merges that result in non-categorical dtypes will likely have higher memory usage. Use `.astype` or `union_categoricals` to ensure `category` results.

```
In [185]: from pandas.api.types import union_categoricals

# same categories
In [186]: s1 = pd.Series(["a", "b"], dtype="category")

In [187]: s2 = pd.Series(["a", "b", "a"], dtype="category")

In [188]: pd.concat([s1, s2])
Out[188]:
0    a
1    b
0    a
1    b
2    a
dtype: category
Categories (2, object): ['a', 'b']

# different categories
In [189]: s3 = pd.Series(["b", "c"], dtype="category")

In [190]: pd.concat([s1, s3])
Out[190]:
0    a
1    b
0    b
1    c
dtype: object

# Output dtype is inferred based on categories values
In [191]: int_cats = pd.Series([1, 2], dtype="category")

In [192]: float_cats = pd.Series([3.0, 4.0], dtype="category")

In [193]: pd.concat([int_cats, float_cats])
Out[193]:
0    1.0
1    2.0
0    3.0
1    4.0
dtype: float64

In [194]: pd.concat([s1, s3]).astype("category")
Out[194]:
0    a
1    b
0    b
1    c
dtype: category
Categories (3, object): ['a', 'b', 'c']

In [195]: union_categoricals([s1.array, s3.array])
Out[195]:
```

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```
['a', 'b', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
```

The following table summarizes the results of merging `Categoricals`:

arg1	arg2	identical	result
category	category	True	category
category (object)	category (object)	False	object (dtype is inferred)
category (int)	category (float)	False	float (dtype is inferred)

See also the section on *merge dtypes* for notes about preserving merge dtypes and performance.

Unioning

If you want to combine categoricals that do not necessarily have the same categories, the *union_categoricals()* function will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```
In [196]: from pandas.api.types import union_categoricals

In [197]: a = pd.Categorical(["b", "c"])

In [198]: b = pd.Categorical(["a", "b"])

In [199]: union_categoricals([a, b])
Out[199]:
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']
```

By default, the resulting categories will be ordered as they appear in the data. If you want the categories to be lexsorted, use `sort_categories=True` argument.

```
In [200]: union_categoricals([a, b], sort_categories=True)
Out[200]:
['b', 'c', 'a', 'b']
Categories (3, object): ['a', 'b', 'c']
```

`union_categoricals` also works with the "easy" case of combining two categoricals of the same categories and order information (e.g. what you could also `append` for).

```
In [201]: a = pd.Categorical(["a", "b"], ordered=True)

In [202]: b = pd.Categorical(["a", "b", "a"], ordered=True)

In [203]: union_categoricals([a, b])
Out[203]:
['a', 'b', 'a', 'b', 'a']
Categories (2, object): ['a' < 'b']
```

The below raises `TypeError` because the categories are ordered and not identical.

```
In [1]: a = pd.Categorical(["a", "b"], ordered=True)
In [2]: b = pd.Categorical(["a", "b", "c"], ordered=True)
In [3]: union_categoricals([a, b])
```

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```
Out[3]:
TypeError: to union ordered Categoricals, all categories must be the same
```

Ordered categoricals with different categories or orderings can be combined by using the `ignore_ordered=True` argument.

```
In [204]: a = pd.Categorical(["a", "b", "c"], ordered=True)

In [205]: b = pd.Categorical(["c", "b", "a"], ordered=True)

In [206]: union_categoricals([a, b], ignore_order=True)
Out[206]:
['a', 'b', 'c', 'c', 'b', 'a']
Categories (3, object): ['a', 'b', 'c']
```

`union_categoricals()` also works with a `CategoricalIndex`, or `Series` containing categorical data, but note that the resulting array will always be a plain `Categorical`:

```
In [207]: a = pd.Series(["b", "c"], dtype="category")

In [208]: b = pd.Series(["a", "b"], dtype="category")

In [209]: union_categoricals([a, b])
Out[209]:
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']
```

Note: `union_categoricals` may recode the integer codes for categories when combining categoricals. This is likely what you want, but if you are relying on the exact numbering of the categories, be aware.

```
In [210]: c1 = pd.Categorical(["b", "c"])

In [211]: c2 = pd.Categorical(["a", "b"])

In [212]: c1
Out[212]:
['b', 'c']
Categories (2, object): ['b', 'c']

# "b" is coded to 0
In [213]: c1.codes
Out[213]: array([0, 1], dtype=int8)

In [214]: c2
Out[214]:
['a', 'b']
Categories (2, object): ['a', 'b']

# "b" is coded to 1
In [215]: c2.codes
Out[215]: array([0, 1], dtype=int8)

In [216]: c = union_categoricals([c1, c2])

In [217]: c
```

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```
Out[217]:
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']

# "b" is coded to 0 throughout, same as c1, different from c2
In [218]: c.codes
Out[218]: array([0, 1, 2, 0], dtype=int8)
```

2.12.9 Getting data in/out

You can write data that contains `category` dtypes to a `HDFStore`. See *here* for an example and caveats.

It is also possible to write data to and reading data from *Stata* format files. See *here* for an example and caveats.

Writing to a CSV file will convert the data, effectively removing any information about the categorical (categories and ordering). So if you read back the CSV file you have to convert the relevant columns back to `category` and assign the right categories and categories ordering.

```
In [219]: import io

In [220]: s = pd.Series(pd.Categorical(["a", "b", "b", "a", "a", "d"]))

# rename the categories
In [221]: s.cat.categories = ["very good", "good", "bad"]

# reorder the categories and add missing categories
In [222]: s = s.cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [223]: df = pd.DataFrame({"cats": s, "vals": [1, 2, 3, 4, 5, 6]})

In [224]: csv = io.StringIO()

In [225]: df.to_csv(csv)

In [226]: df2 = pd.read_csv(io.StringIO(csv.getvalue()))

In [227]: df2.dtypes
Out[227]:
Unnamed: 0     int64
cats          object
vals           int64
dtype: object

In [228]: df2["cats"]
Out[228]:
0    very good
1         good
2         good
3    very good
4    very good
5          bad
Name: cats, dtype: object

# Redo the category
```

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```
In [229]: df2["cats"] = df2["cats"].astype("category")

In [230]: df2["cats"].cat.set_categories(
   .....:     ["very bad", "bad", "medium", "good", "very good"], inplace=True
   .....: )
   .....:

In [231]: df2.dtypes
Out[231]:
Unnamed: 0       int64
cats          category
vals             int64
dtype: object

In [232]: df2["cats"]
Out[232]:
0    very good
1         good
2         good
3    very good
4    very good
5          bad
Name: cats, dtype: category
Categories (5, object): ['very bad', 'bad', 'medium', 'good', 'very good']
```

The same holds for writing to a SQL database with `to_sql`.

2.12.10 Missing data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the *Missing Data section*.

Missing values should **not** be included in the Categorical's `categories`, only in the `values`. Instead, it is understood that NaN is different, and is always a possibility. When working with the Categorical's `codes`, missing values will always have a code of `-1`.

```
In [233]: s = pd.Series(["a", "b", np.nan, "a"], dtype="category")

# only two categories
In [234]: s
Out[234]:
0      a
1      b
2    NaN
3      a
dtype: category
Categories (2, object): ['a', 'b']

In [235]: s.cat.codes
Out[235]:
0    0
1    1
2   -1
3    0
dtype: int8
```

Methods for working with missing data, e.g. *isna()*, *fillna()*, *dropna()*, all work normally:

```
In [236]: s = pd.Series(["a", "b", np.nan], dtype="category")

In [237]: s
Out[237]:
0      a
1      b
2    NaN
dtype: category
Categories (2, object): ['a', 'b']

In [238]: pd.isna(s)
Out[238]:
0    False
1    False
2     True
dtype: bool

In [239]: s.fillna("a")
Out[239]:
0    a
1    b
2    a
dtype: category
Categories (2, object): ['a', 'b']
```

2.12.11 Differences to R's `factor`

The following differences to R's factor functions can be observed:

- R's `levels` are named `categories`.
- R's `levels` are always of type string, while `categories` in pandas can be of any dtype.
- It's not possible to specify labels at creation time. Use `s.cat.rename_categories(new_labels)` afterwards.
- In contrast to R's `factor` function, using categorical data as the sole input to create a new categorical series will *not* remove unused categories but create a new categorical series which is equal to the passed in one!
- R allows for missing values to be included in its `levels` (pandas' `categories`). pandas does not allow `NaN` categories, but missing values can still be in the `values`.

2.12.12 Gotchas

Memory usage

The memory usage of a `Categorical` is proportional to the number of categories plus the length of the data. In contrast, an `object` dtype is a constant times the length of the data.

```
In [240]: s = pd.Series(["foo", "bar"] * 1000)

# object dtype
In [241]: s.nbytes
Out[241]: 16000
```

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```
# category dtype
In [242]: s.astype("category").nbytes
Out[242]: 2016
```

Note: If the number of categories approaches the length of the data, the `Categorical` will use nearly the same or more memory than an equivalent `object` dtype representation.

```
In [243]: s = pd.Series(["foo%04d" % i for i in range(2000)])

# object dtype
In [244]: s.nbytes
Out[244]: 16000

# category dtype
In [245]: s.astype("category").nbytes
Out[245]: 20000
```

`Categorical` is not a `numpy` array

Currently, categorical data and the underlying `Categorical` is implemented as a Python object and not as a low-level NumPy array dtype. This leads to some problems.

NumPy itself doesn't know about the new `dtype`:

```
In [246]: try:
   .....:     np.dtype("category")
   .....: except TypeError as e:
   .....:     print("TypeError:", str(e))
   .....:
TypeError: data type 'category' not understood

In [247]: dtype = pd.Categorical(["a"]).dtype

In [248]: try:
   .....:     np.dtype(dtype)
   .....: except TypeError as e:
   .....:     print("TypeError:", str(e))
   .....:
TypeError: Cannot interpret 'CategoricalDtype(categories=['a'], ordered=False)' as a␣
↪data type
```

Dtype comparisons work:

```
In [249]: dtype == np.str_
Out[249]: False

In [250]: np.str_ == dtype
Out[250]: False
```

To check if a Series contains Categorical data, use `hasattr(s, 'cat')`:

```
In [251]: hasattr(pd.Series(["a"], dtype="category"), "cat")
Out[251]: True

In [252]: hasattr(pd.Series(["a"]), "cat")
Out[252]: False
```

Using NumPy functions on a `Series` of type `category` should not work as `Categoricals` are not numeric data (even in the case that `.categories` is numeric).

```
In [253]: s = pd.Series(pd.Categorical([1, 2, 3, 4]))

In [254]: try:
   .....:     np.sum(s)
   .....: except TypeError as e:
   .....:     print("TypeError:", str(e))
   .....:
TypeError: 'Categorical' does not implement reduction 'sum'
```

Note: If such a function works, please file a bug at https://github.com/pandas-dev/pandas!

dtype in apply

pandas currently does not preserve the dtype in apply functions: If you apply along rows you get a `Series` of `object` `dtype` (same as getting a row -> getting one element will return a basic type) and applying along columns will also convert to object. `NaN` values are unaffected. You can use `fillna` to handle missing values before applying a function.

```
In [255]: df = pd.DataFrame(
   .....:     {
   .....:         "a": [1, 2, 3, 4],
   .....:         "b": ["a", "b", "c", "d"],
   .....:         "cats": pd.Categorical([1, 2, 3, 2]),
   .....:     }
   .....: )
   .....:

In [256]: df.apply(lambda row: type(row["cats"]), axis=1)
Out[256]:
0    <class 'int'>
1    <class 'int'>
2    <class 'int'>
3    <class 'int'>
dtype: object

In [257]: df.apply(lambda col: col.dtype, axis=0)
Out[257]:
a          int64
b         object
cats    category
dtype: object
```

Categorical index

`CategoricalIndex` is a type of index that is useful for supporting indexing with duplicates. This is a container around a `Categorical` and allows efficient indexing and storage of an index with a large number of duplicated elements. See the *advanced indexing docs* for a more detailed explanation.

Setting the index will create a `CategoricalIndex`:

```
In [258]: cats = pd.Categorical([1, 2, 3, 4], categories=[4, 2, 3, 1])

In [259]: strings = ["a", "b", "c", "d"]

In [260]: values = [4, 2, 3, 1]

In [261]: df = pd.DataFrame({"strings": strings, "values": values}, index=cats)

In [262]: df.index
Out[262]: CategoricalIndex([1, 2, 3, 4], categories=[4, 2, 3, 1], ordered=False,␣
↪dtype='category')

# This now sorts by the categories order
In [263]: df.sort_index()
Out[263]:
  strings  values
4       d       1
2       b       2
3       c       3
1       a       4
```

Side effects

Constructing a `Series` from a `Categorical` will not copy the input `Categorical`. This means that changes to the `Series` will in most cases change the original `Categorical`:

```
In [264]: cat = pd.Categorical([1, 2, 3, 10], categories=[1, 2, 3, 4, 10])

In [265]: s = pd.Series(cat, name="cat")

In [266]: cat
Out[266]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [267]: s.iloc[0:2] = 10

In [268]: cat
Out[268]:
[10, 10, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [269]: df = pd.DataFrame(s)

In [270]: df["cat"].cat.categories = [1, 2, 3, 4, 5]

In [271]: cat
Out[271]:
```

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```
[5, 5, 3, 5]
Categories (5, int64): [1, 2, 3, 4, 5]
```

Use `copy=True` to prevent such a behaviour or simply don't reuse `Categoricals`:

```
In [272]: cat = pd.Categorical([1, 2, 3, 10], categories=[1, 2, 3, 4, 10])

In [273]: s = pd.Series(cat, name="cat", copy=True)

In [274]: cat
Out[274]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [275]: s.iloc[0:2] = 10

In [276]: cat
Out[276]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

Note: This also happens in some cases when you supply a NumPy array instead of a `Categorical`: using an int array (e.g. `np.array([1,2,3,4])`) will exhibit the same behavior, while using a string array (e.g. `np.array(["a","b","c","a"])`) will not.

2.13 Nullable integer data type

New in version 0.24.0.

Note: IntegerArray is currently experimental. Its API or implementation may change without warning.

Changed in version 1.0.0: Now uses `pandas.NA` as the missing value rather than `numpy.nan`.

In *Working with missing data*, we saw that pandas primarily uses `NaN` to represent missing data. Because `NaN` is a float, this forces an array of integers with any missing values to become floating point. In some cases, this may not matter much. But if your integer column is, say, an identifier, casting to float can be problematic. Some integers cannot even be represented as floating point numbers.

2.13.1 Construction

pandas can represent integer data with possibly missing values using *`arrays.IntegerArray`*. This is an *extension types* implemented within pandas.

```
In [1]: arr = pd.array([1, 2, None], dtype=pd.Int64Dtype())

In [2]: arr
Out[2]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

Or the string alias `"Int64"` (note the capital `"I"`, to differentiate from NumPy's `'int64'` dtype:

```
In [3]: pd.array([1, 2, np.nan], dtype="Int64")
Out[3]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

All NA-like values are replaced with `pandas.NA`.

```
In [4]: pd.array([1, 2, np.nan, None, pd.NA], dtype="Int64")
Out[4]:
<IntegerArray>
[1, 2, <NA>, <NA>, <NA>]
Length: 5, dtype: Int64
```

This array can be stored in a *DataFrame* or *Series* like any NumPy array.

```
In [5]: pd.Series(arr)
Out[5]:
0       1
1       2
2    <NA>
dtype: Int64
```

You can also pass the list-like object to the *Series* constructor with the dtype.

Warning: Currently *pandas.array()* and *pandas.Series()* use different rules for dtype inference. *pandas.array()* will infer a nullable- integer dtype

```
In [6]: pd.array([1, None])
Out[6]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64

In [7]: pd.array([1, 2])
Out[7]:
<IntegerArray>
[1, 2]
Length: 2, dtype: Int64
```

For backwards-compatibility, *Series* infers these as either integer or float dtype

```
In [8]: pd.Series([1, None])
Out[8]:
0    1.0
1    NaN
dtype: float64

In [9]: pd.Series([1, 2])
Out[9]:
0    1
1    2
dtype: int64
```

We recommend explicitly providing the dtype to avoid confusion.

```
In [10]: pd.array([1, None], dtype="Int64")
Out[10]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64

In [11]: pd.Series([1, None], dtype="Int64")
Out[11]:
0       1
1    <NA>
dtype: Int64
```

In the future, we may provide an option for *Series* to infer a nullable-integer dtype.

2.13.2 Operations

Operations involving an integer array will behave similar to NumPy arrays. Missing values will be propagated, and the data will be coerced to another dtype if needed.

```
In [12]: s = pd.Series([1, 2, None], dtype="Int64")

# arithmetic
In [13]: s + 1
Out[13]:
0       2
1       3
2    <NA>
dtype: Int64

# comparison
In [14]: s == 1
Out[14]:
0     True
1    False
2     <NA>
dtype: boolean

# indexing
In [15]: s.iloc[1:3]
Out[15]:
1       2
2    <NA>
dtype: Int64

# operate with other dtypes
In [16]: s + s.iloc[1:3].astype("Int8")
Out[16]:
0    <NA>
1       4
2    <NA>
dtype: Int64

# coerce when needed
In [17]: s + 0.01
Out[17]:
```

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```
0    1.01
1    2.01
2    <NA>
dtype: Float64
```

These dtypes can operate as part of `DataFrame`.

```
In [18]: df = pd.DataFrame({"A": s, "B": [1, 1, 3], "C": list("aab")})

In [19]: df
Out[19]:
      A  B  C
0     1  1  a
1     2  1  a
2  <NA>  3  b

In [20]: df.dtypes
Out[20]:
A     Int64
B     int64
C    object
dtype: object
```

These dtypes can be merged & reshaped & casted.

```
In [21]: pd.concat([df[["A"]], df[["B", "C"]]], axis=1).dtypes
Out[21]:
A     Int64
B     int64
C    object
dtype: object

In [22]: df["A"].astype(float)
Out[22]:
0    1.0
1    2.0
2    NaN
Name: A, dtype: float64
```

Reduction and groupby operations such as 'sum' work as well.

```
In [23]: df.sum()
Out[23]:
A      3
B      5
C    aab
dtype: object

In [24]: df.groupby("B").A.sum()
Out[24]:
B
1    3
3    0
Name: A, dtype: Int64
```

2.13.3 Scalar NA Value

arrays.IntegerArray uses pandas.NA as its scalar missing value. Slicing a single element that's missing will return pandas.NA

```
In [25]: a = pd.array([1, None], dtype="Int64")

In [26]: a[1]
Out[26]: <NA>
```

2.14 Nullable Boolean data type

New in version 1.0.0.

2.14.1 Indexing with NA values

pandas allows indexing with NA values in a boolean array, which are treated as False.

Changed in version 1.0.2.

```
In [1]: s = pd.Series([1, 2, 3])

In [2]: mask = pd.array([True, False, pd.NA], dtype="boolean")

In [3]: s[mask]
Out[3]:
0    1
dtype: int64
```

If you would prefer to keep the NA values you can manually fill them with fillna(True).

```
In [4]: s[mask.fillna(True)]
Out[4]:
0    1
2    3
dtype: int64
```

2.14.2 Kleene logical operations

arrays.BooleanArray implements Kleene Logic (sometimes called three-value logic) for logical operations like & (and), | (or) and ^ (exclusive-or).

This table demonstrates the results for every combination. These operations are symmetrical, so flipping the left- and right-hand side makes no difference in the result.

Expression	Result
`True & True`	`True`
`True & False`	`False`
`True & NA`	`NA`
`False & False`	`False`
`False & NA`	`False`
`NA & NA`	`NA`
`True | True`	`True`
`True | False`	`True`
`True | NA`	`True`
`False | False`	`False`
`False | NA`	`NA`
`NA | NA`	`NA`
`True ^ True`	`False`
`True ^ False`	`True`
`True ^ NA`	`NA`
`False ^ False`	`False`
`False ^ NA`	`NA`
`NA ^ NA`	`NA`

When an `NA` is present in an operation, the output value is `NA` only if the result cannot be determined solely based on the other input. For example, `True | NA` is `True`, because both `True | True` and `True | False` are `True`. In that case, we don't actually need to consider the value of the `NA`.

On the other hand, `True & NA` is `NA`. The result depends on whether the `NA` really is `True` or `False`, since `True & True` is `True`, but `True & False` is `False`, so we can't determine the output.

This differs from how `np.nan` behaves in logical operations. pandas treated `np.nan` is *always false in the output*.

In `or`

```
In [5]: pd.Series([True, False, np.nan], dtype="object") | True
Out[5]:
0     True
1     True
2    False
dtype: bool

In [6]: pd.Series([True, False, np.nan], dtype="boolean") | True
Out[6]:
0    True
1    True
2    True
dtype: boolean
```

In `and`

```
In [7]: pd.Series([True, False, np.nan], dtype="object") & True
Out[7]:
0     True
1    False
2    False
dtype: bool

In [8]: pd.Series([True, False, np.nan], dtype="boolean") & True
```

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```
Out[8]:
0     True
1    False
2     <NA>
dtype: boolean
```

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2.15 Visualization

We use the standard convention for referencing the matplotlib API:

```
In [1]: import matplotlib.pyplot as plt

In [2]: plt.close("all")
```

We provide the basics in pandas to easily create decent looking plots. See the ecosystem section for visualization libraries that go beyond the basics documented here.

Note: All calls to `np.random` are seeded with 123456.

2.15.1 Basic plotting: `plot`

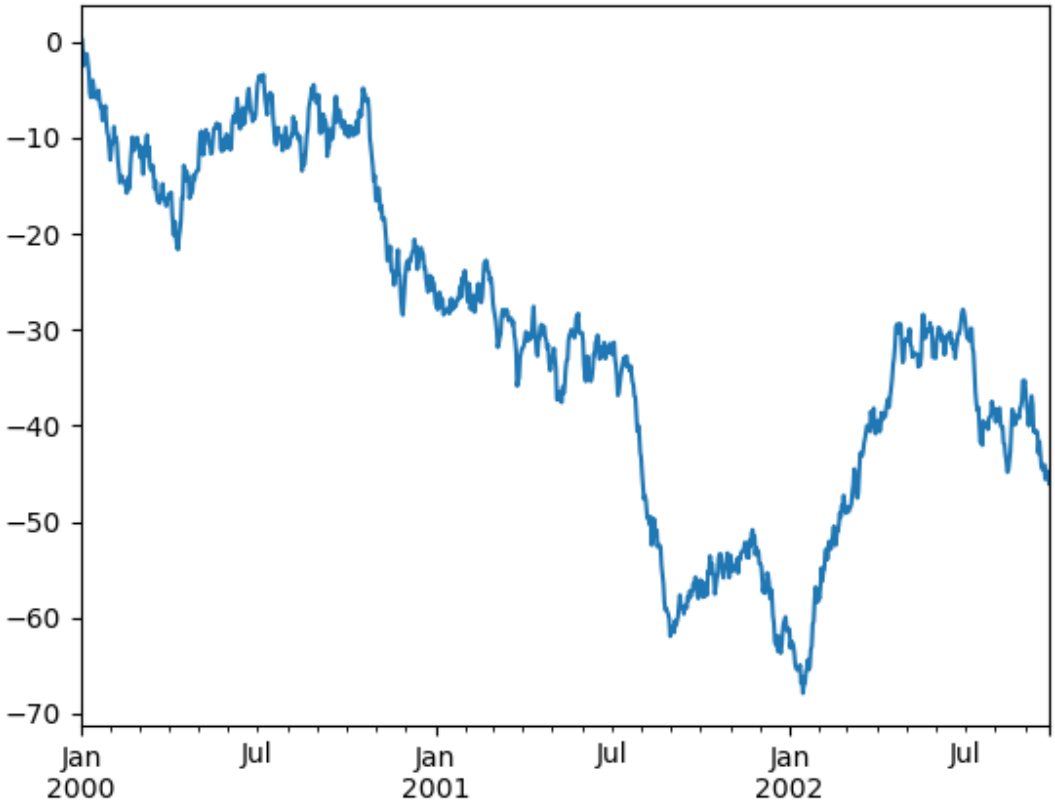
We will demonstrate the basics, see the *cookbook* for some advanced strategies.

The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot()`:

```
In [3]: ts = pd.Series(np.random.randn(1000), index=pd.date_range("1/1/2000",␣
↪periods=1000))

In [4]: ts = ts.cumsum()

In [5]: ts.plot();
```



If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above.

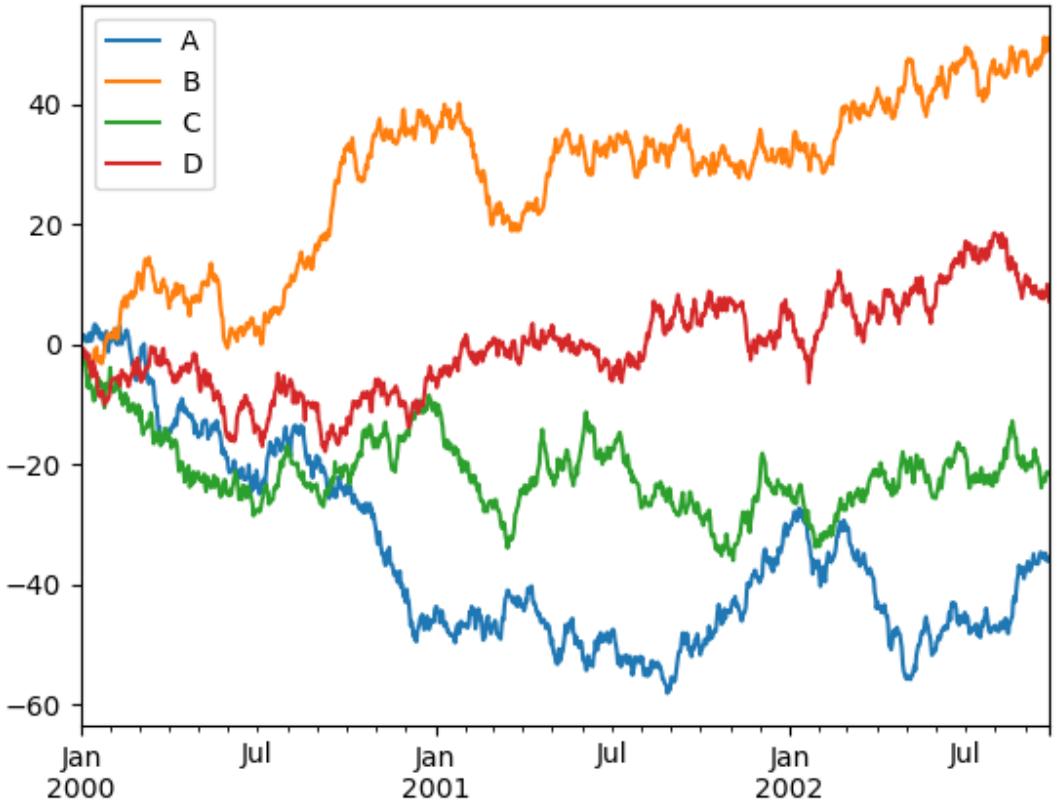
On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```
In [6]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list("ABCD
↪"))

In [7]: df = df.cumsum()

In [8]: plt.figure();

In [9]: df.plot();
```

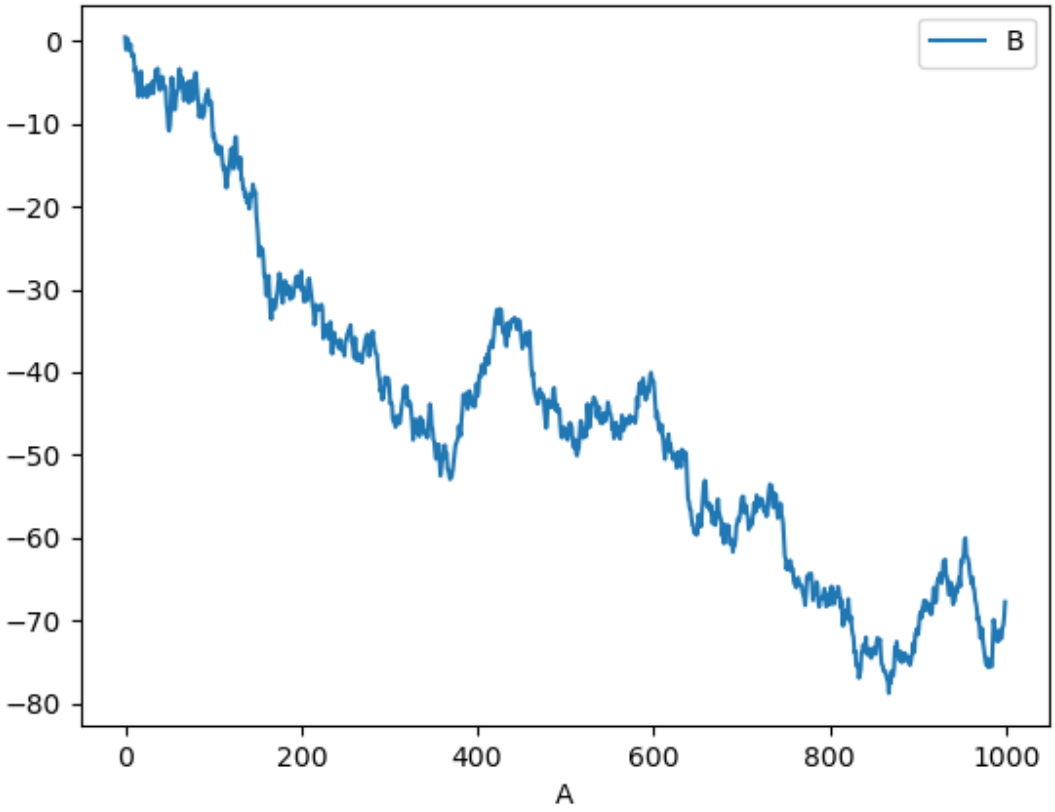


You can plot one column versus another using the `x` and `y` keywords in `plot()`:

```
In [10]: df3 = pd.DataFrame(np.random.randn(1000, 2), columns=["B", "C"]).cumsum()

In [11]: df3["A"] = pd.Series(list(range(len(df))))

In [12]: df3.plot(x="A", y="B");
```



Note: For more formatting and styling options, see *formatting* below.

2.15.2 Other plots

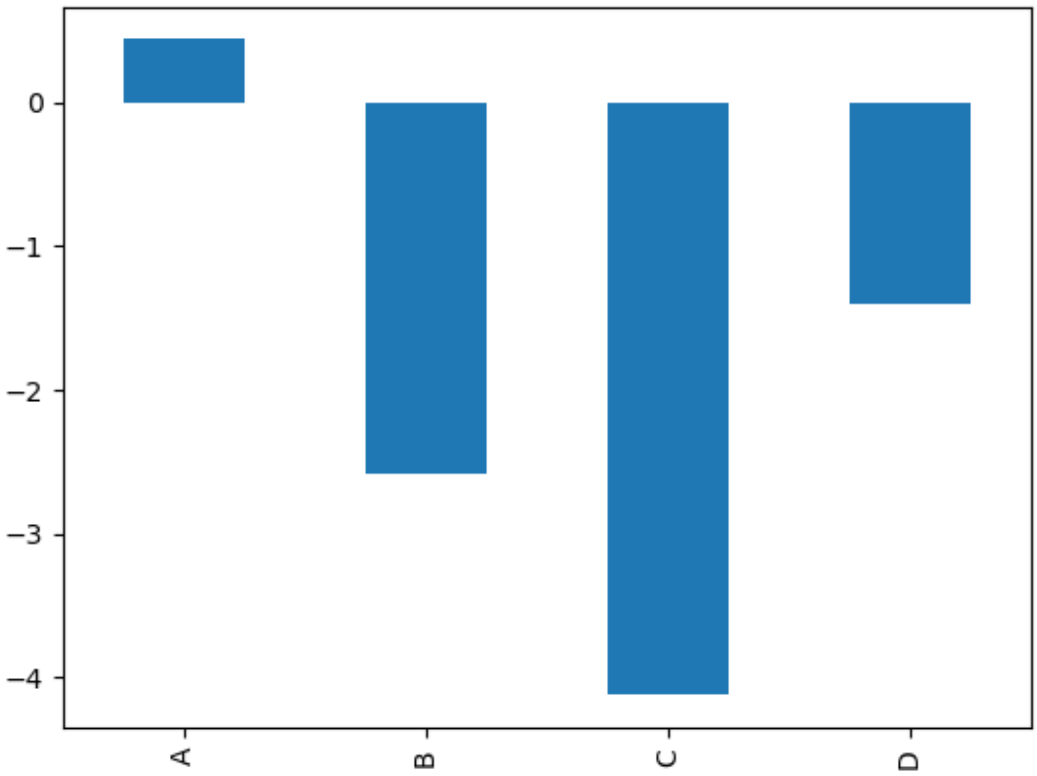
Plotting methods allow for a handful of plot styles other than the default line plot. These methods can be provided as the `kind` keyword argument to `plot()`, and include:

- *'bar'* or *'barh'* for bar plots
- *'hist'* for histogram
- *'box'* for boxplot
- *'kde'* or *'density'* for density plots
- *'area'* for area plots
- *'scatter'* for scatter plots
- *'hexbin'* for hexagonal bin plots
- *'pie'* for pie plots

For example, a bar plot can be created the following way:

```
In [13]: plt.figure();

In [14]: df.iloc[5].plot(kind="bar");
```



You can also create these other plots using the methods `DataFrame.plot.<kind>` instead of providing the `kind` keyword argument. This makes it easier to discover plot methods and the specific arguments they use:

```
In [15]: df = pd.DataFrame()

In [16]: df.plot.<TAB>  # noqa: E225, E999
df.plot.area     df.plot.barh     df.plot.density  df.plot.hist     df.plot.line
↪df.plot.scatter
df.plot.bar      df.plot.box      df.plot.hexbin   df.plot.kde      df.plot.pie
```

In addition to these `kind` s, there are the *DataFrame.hist()*, and *DataFrame.boxplot()* methods, which use a separate interface.

Finally, there are several *plotting functions* in `pandas.plotting` that take a `Series` or `DataFrame` as an argument. These include:

- *Scatter Matrix*
- *Andrews Curves*
- *Parallel Coordinates*
- *Lag Plot*

- *Autocorrelation Plot*
- *Bootstrap Plot*
- *RadViz*

Plots may also be adorned with *errorbars* or *tables*.

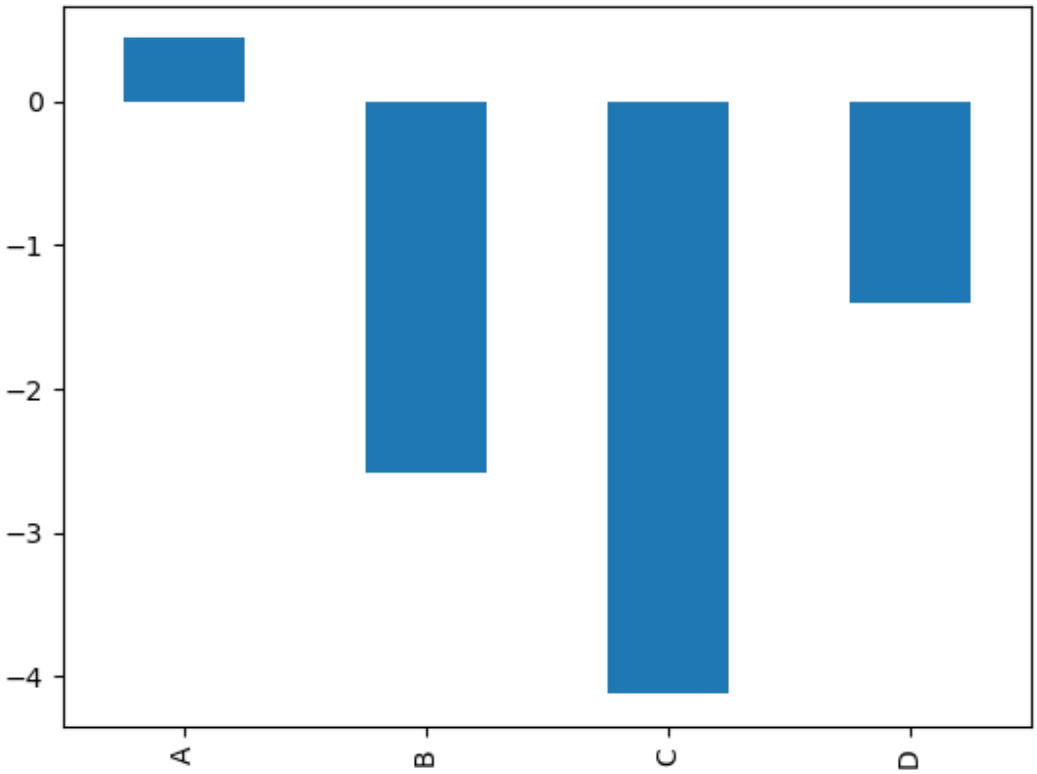
Bar plots

For labeled, non-time series data, you may wish to produce a bar plot:

```
In [17]: plt.figure();

In [18]: df.iloc[5].plot.bar();

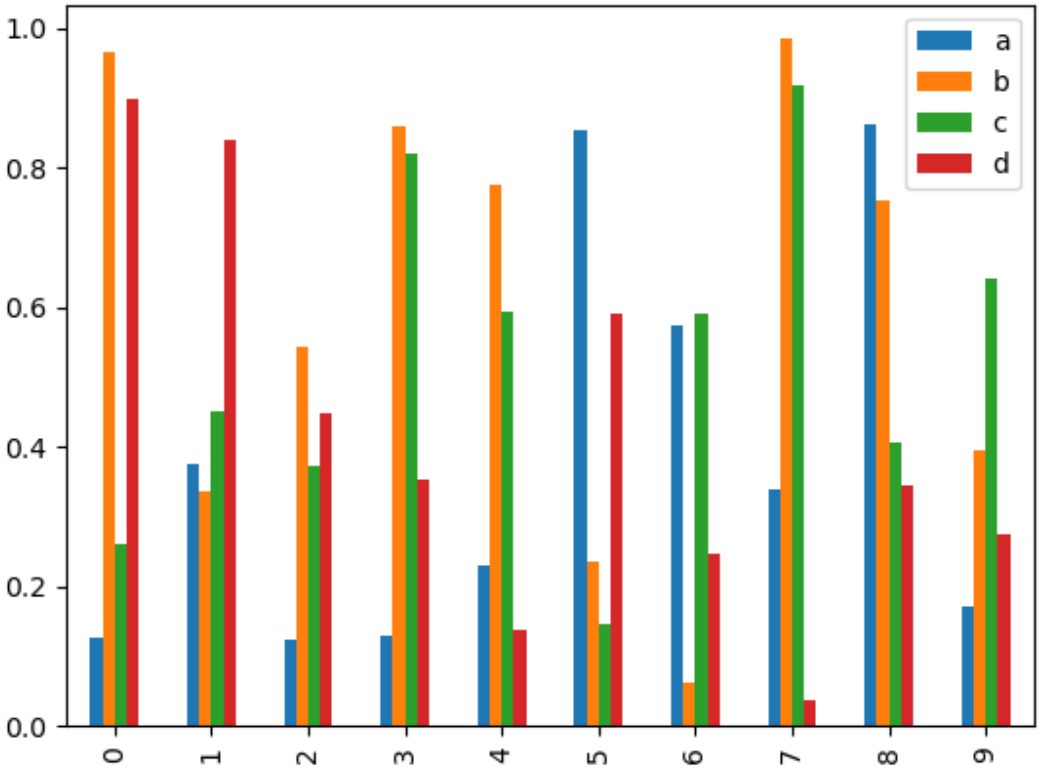
In [19]: plt.axhline(0, color="k");
```



Calling a DataFrame's `plot.bar()` method produces a multiple bar plot:

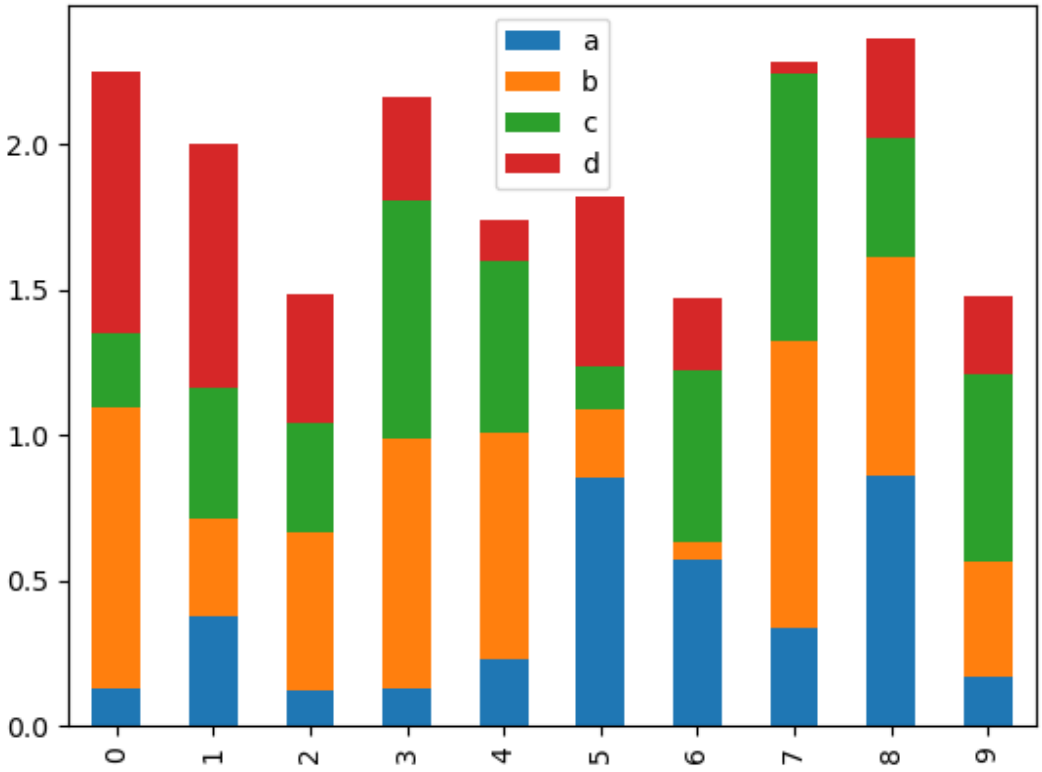
```
In [20]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=["a", "b", "c", "d"])

In [21]: df2.plot.bar();
```



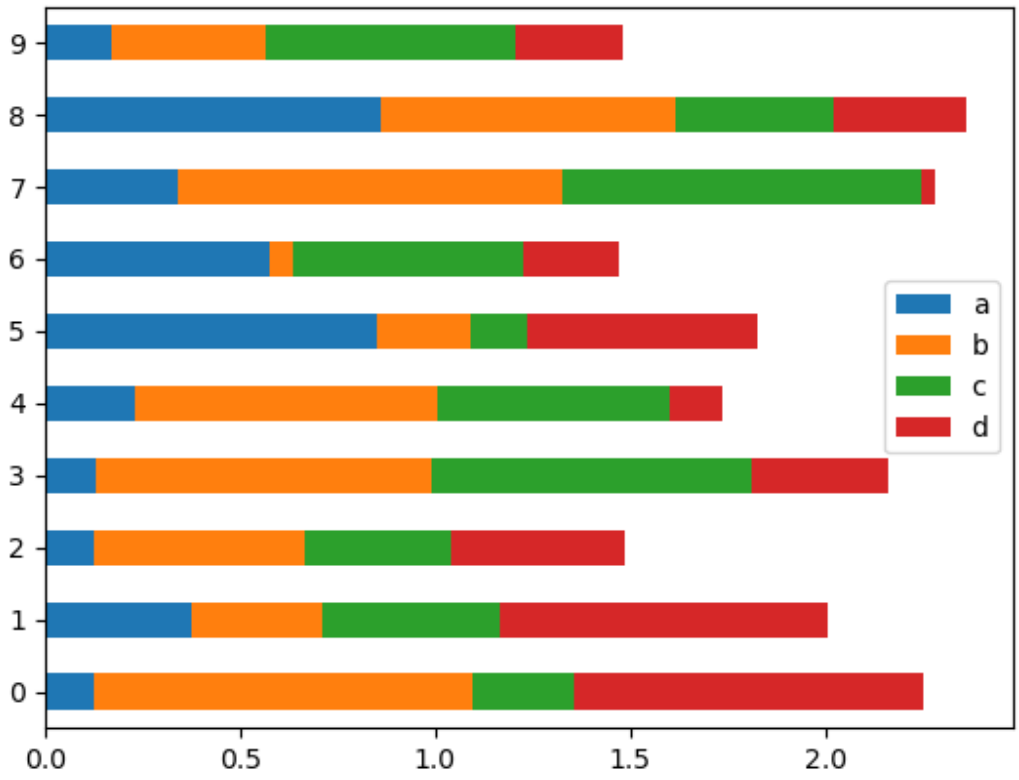
To produce a stacked bar plot, pass `stacked=True`:

```
In [22]: df2.plot.bar(stacked=True);
```



To get horizontal bar plots, use the `barh` method:

```
In [23]: df2.plot.barh(stacked=True);
```



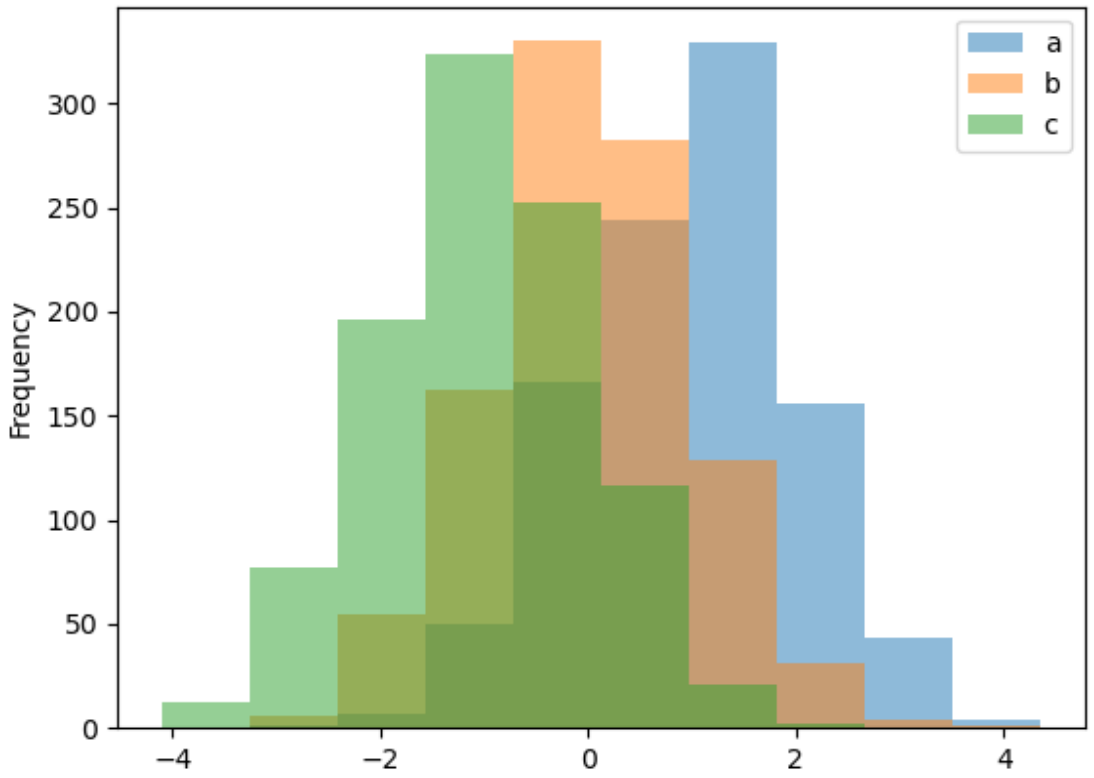
Histograms

Histograms can be drawn by using the `DataFrame.plot.hist()` and `Series.plot.hist()` methods.

```
In [24]: df4 = pd.DataFrame(
   ....:     {
   ....:         "a": np.random.randn(1000) + 1,
   ....:         "b": np.random.randn(1000),
   ....:         "c": np.random.randn(1000) - 1,
   ....:     },
   ....:     columns=["a", "b", "c"],
   ....: )
   ....:

In [25]: plt.figure();

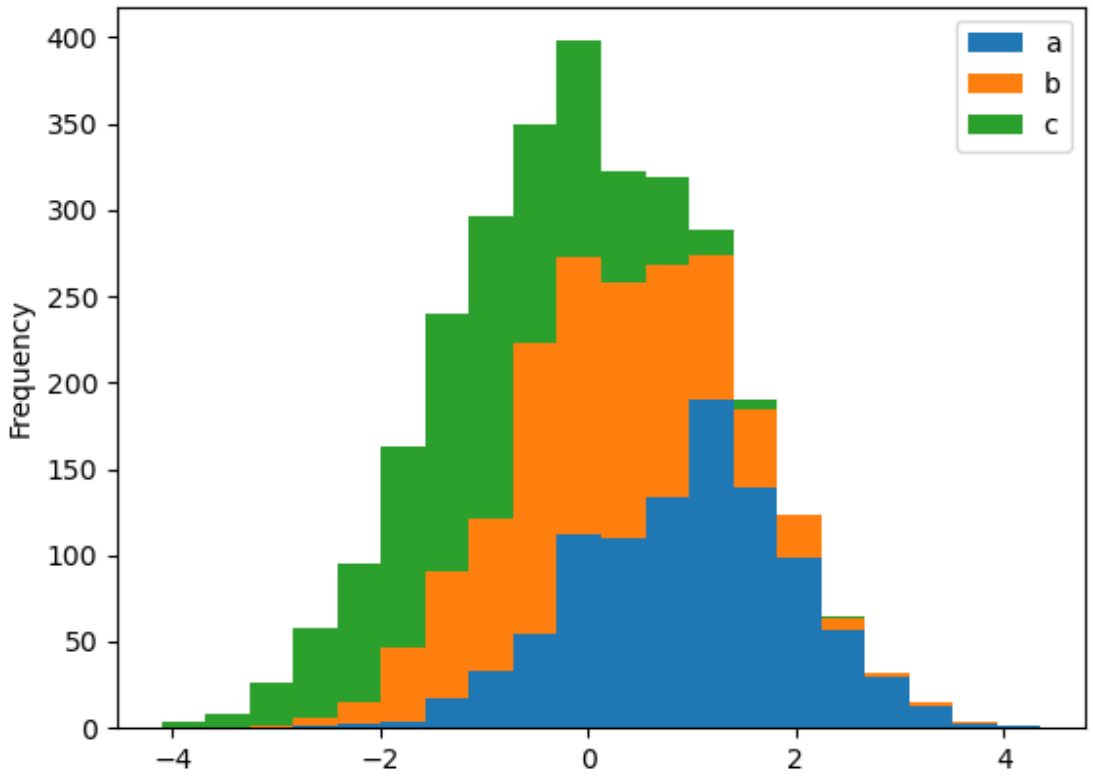
In [26]: df4.plot.hist(alpha=0.5);
```



A histogram can be stacked using `stacked=True`. Bin size can be changed using the `bins` keyword.

```
In [27]: plt.figure();

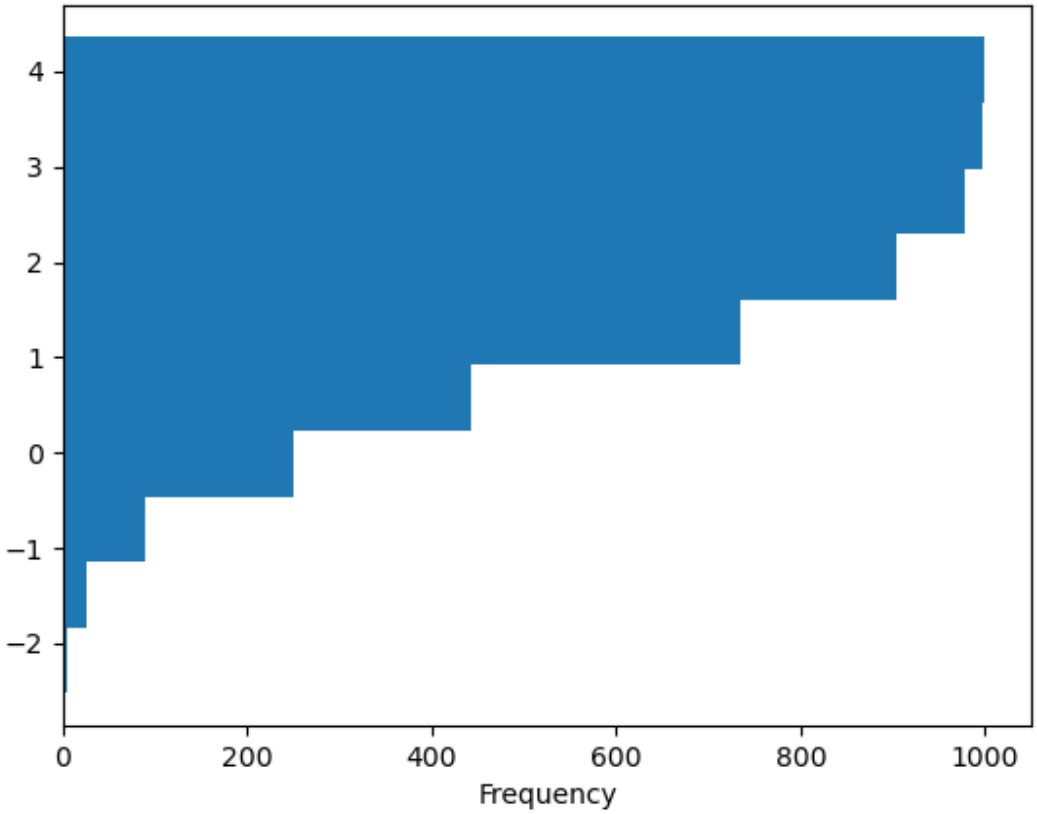
In [28]: df4.plot.hist(stacked=True, bins=20);
```



You can pass other keywords supported by matplotlib `hist`. For example, horizontal and cumulative histograms can be drawn by `orientation='horizontal'` and `cumulative=True`.

```
In [29]: plt.figure();

In [30]: df4["a"].plot.hist(orientation="horizontal", cumulative=True);
```

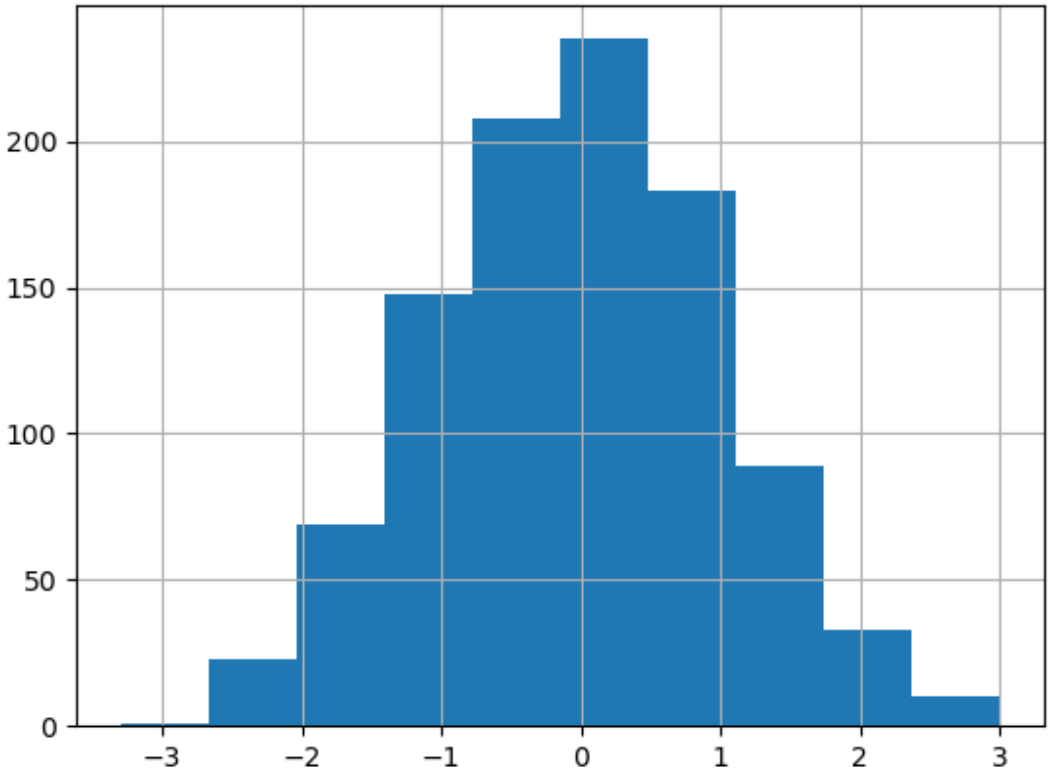


See the `hist` method and the matplotlib hist documentation for more.

The existing interface `DataFrame.hist` to plot histogram still can be used.

```
In [31]: plt.figure();

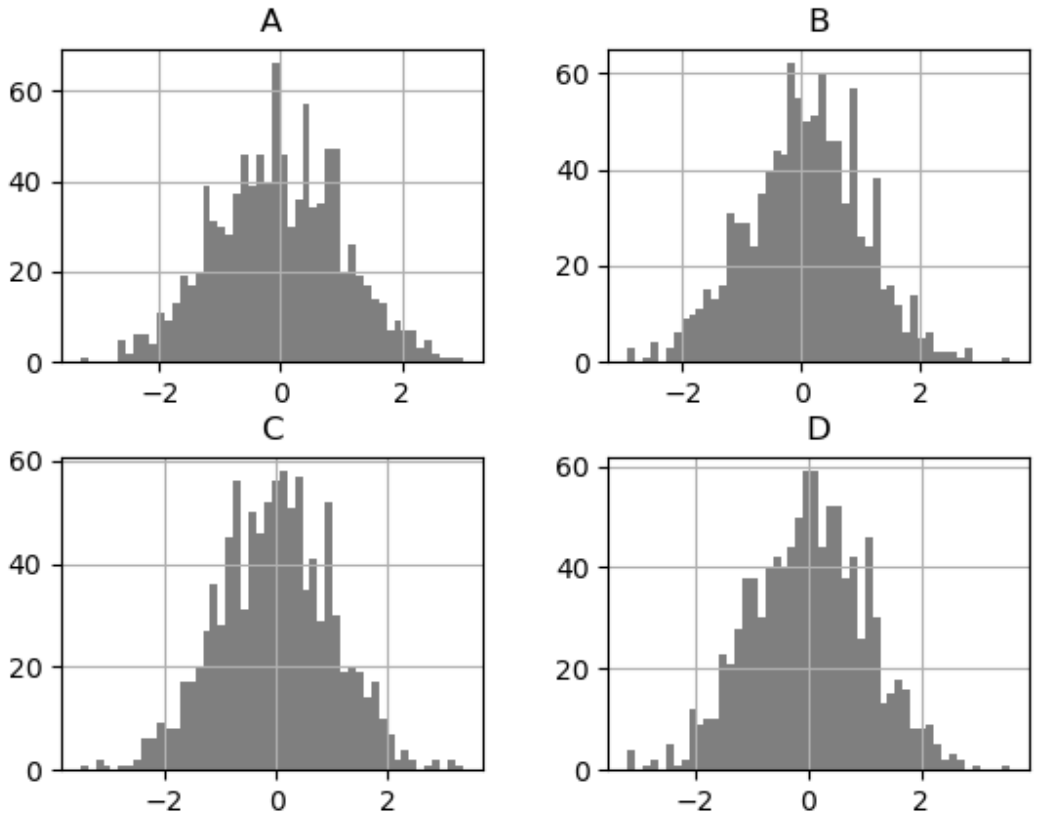
In [32]: df["A"].diff().hist();
```



`DataFrame.hist()` plots the histograms of the columns on multiple subplots:

```
In [33]: plt.figure();

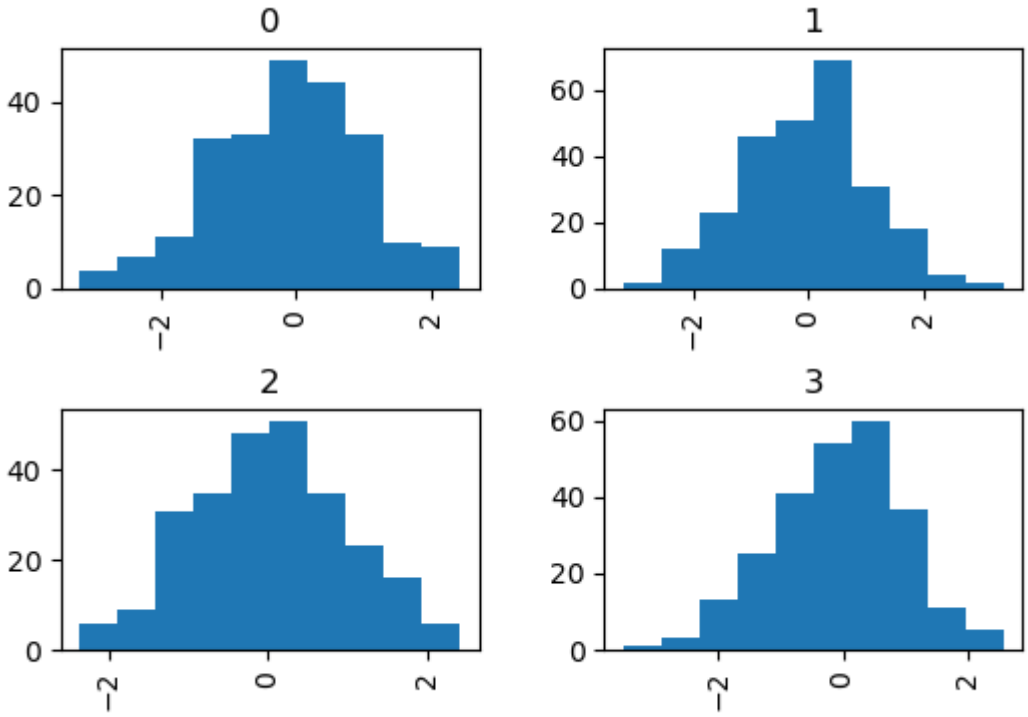
In [34]: df.diff().hist(color="k", alpha=0.5, bins=50);
```



The `by` keyword can be specified to plot grouped histograms:

```
In [35]: data = pd.Series(np.random.randn(1000))

In [36]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4));
```



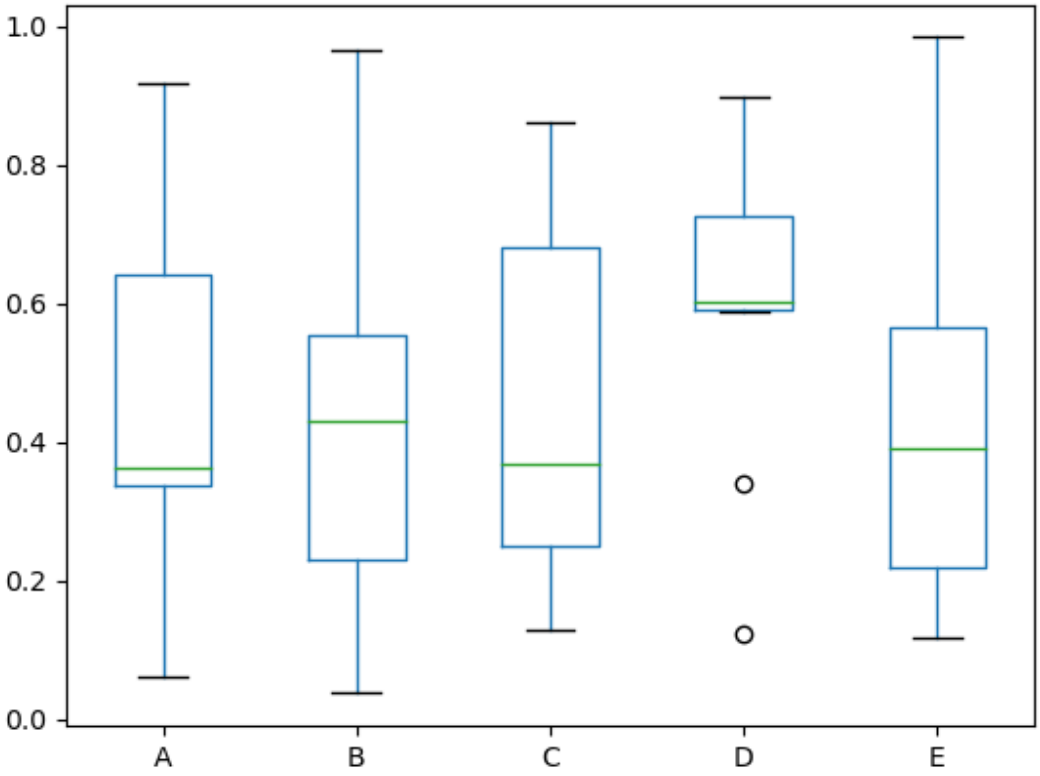
Box plots

Boxplot can be drawn calling `Series.plot.box()` and `DataFrame.plot.box()`, or `DataFrame.boxplot()` to visualize the distribution of values within each column.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on [0,1).

```
In [37]: df = pd.DataFrame(np.random.rand(10, 5), columns=["A", "B", "C", "D", "E"])

In [38]: df.plot.box();
```



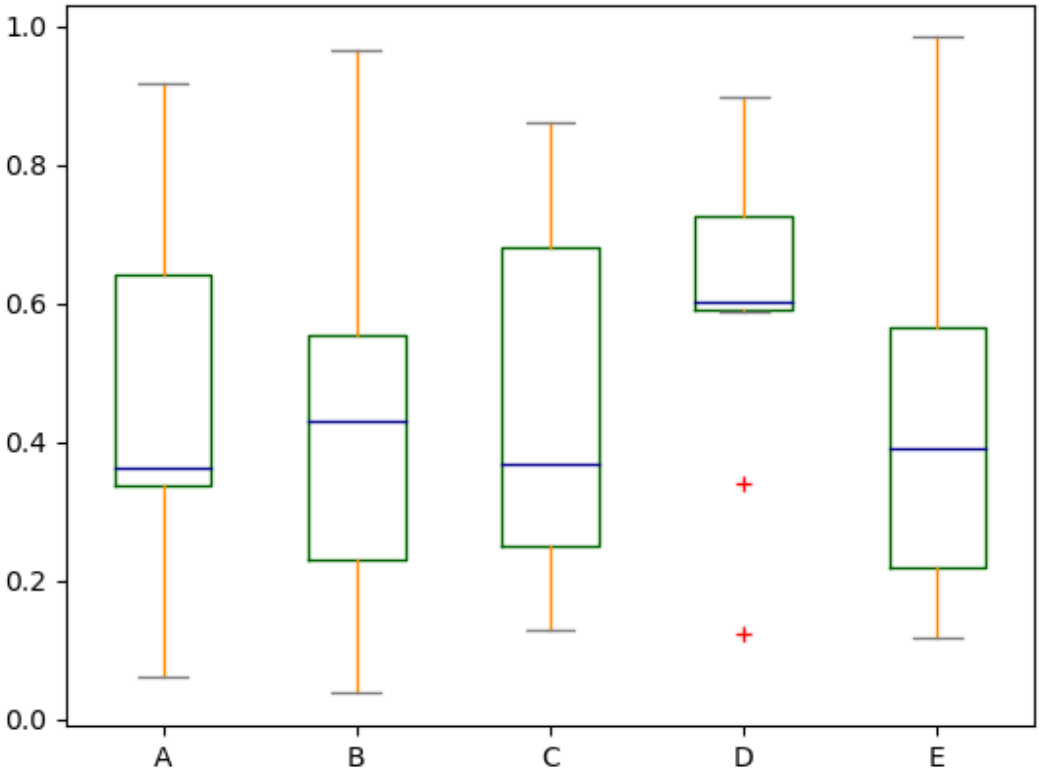
Boxplot can be colorized by passing `color` keyword. You can pass a `dict` whose keys are `boxes`, `whiskers`, `medians` and `caps`. If some keys are missing in the `dict`, default colors are used for the corresponding artists. Also, boxplot has `sym` keyword to specify fliers style.

When you pass other type of arguments via `color` keyword, it will be directly passed to matplotlib for all the `boxes`, `whiskers`, `medians` and `caps` colorization.

The colors are applied to every boxes to be drawn. If you want more complicated colorization, you can get each drawn artists by passing *return_type*.

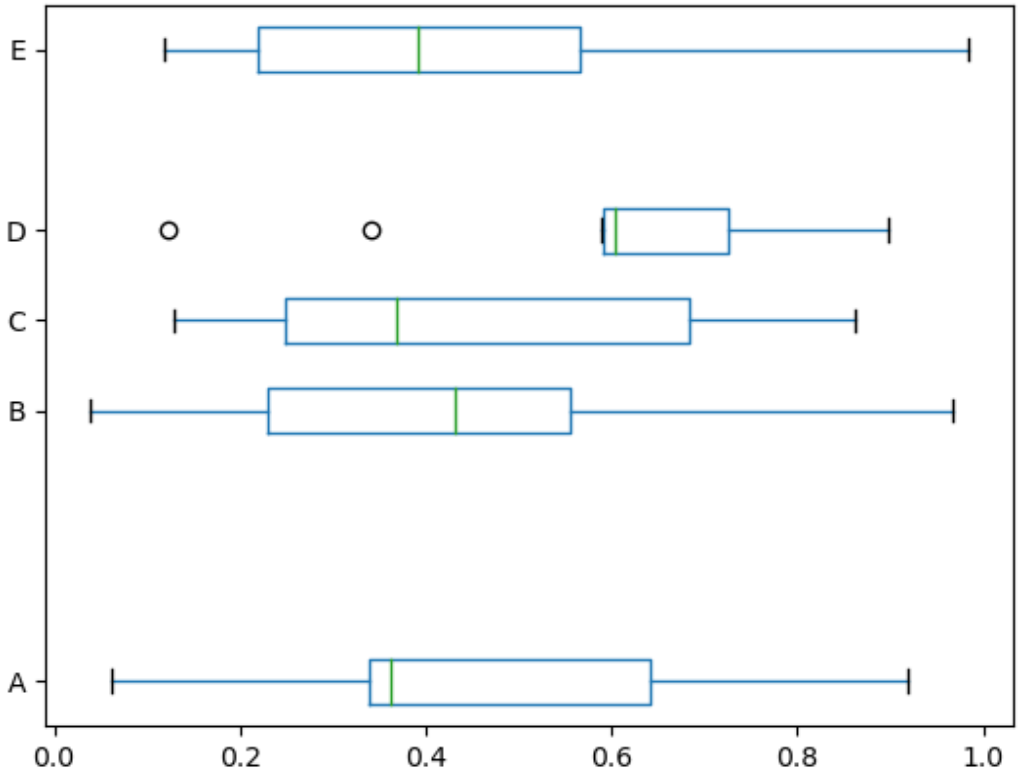
```
In [39]: color = {
   ....:     "boxes": "DarkGreen",
   ....:     "whiskers": "DarkOrange",
   ....:     "medians": "DarkBlue",
   ....:     "caps": "Gray",
   ....: }
   ....:

In [40]: df.plot.box(color=color, sym="r+");
```



Also, you can pass other keywords supported by matplotlib `boxplot`. For example, horizontal and custom-positioned boxplot can be drawn by `vert=False` and `positions` keywords.

```
In [41]: df.plot.box(vert=False, positions=[1, 4, 5, 6, 8]);
```



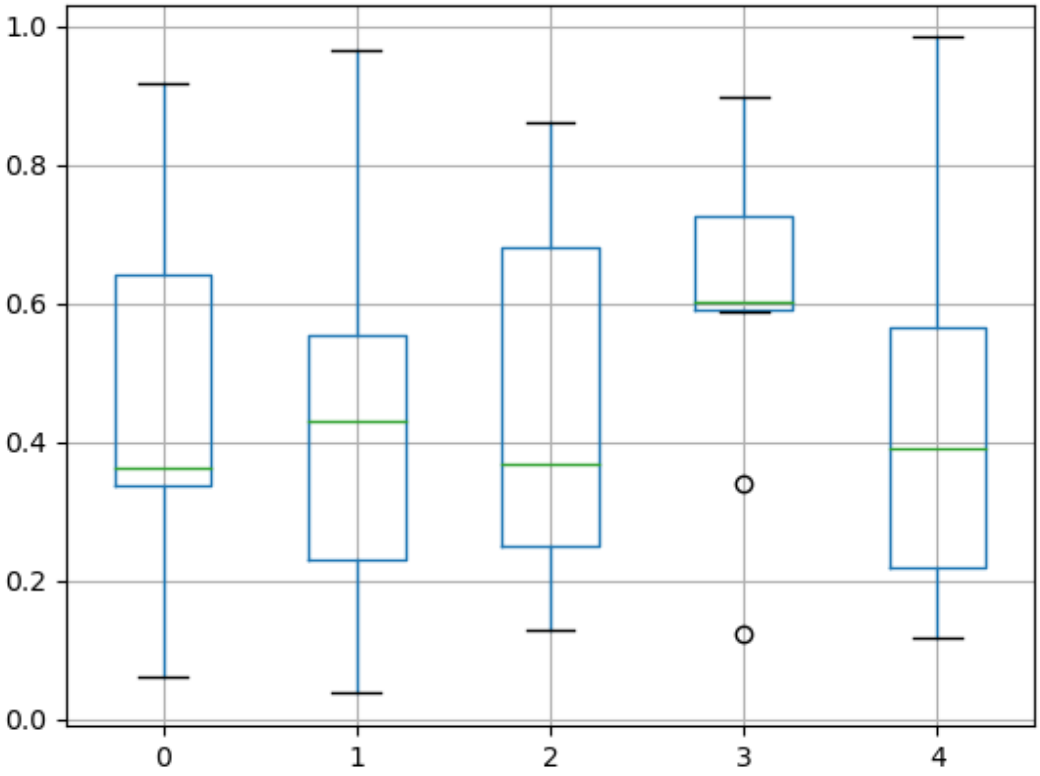
See the `boxplot` method and the matplotlib boxplot documentation for more.

The existing interface `DataFrame.boxplot` to plot boxplot still can be used.

```
In [42]: df = pd.DataFrame(np.random.rand(10, 5))

In [43]: plt.figure();

In [44]: bp = df.boxplot()
```



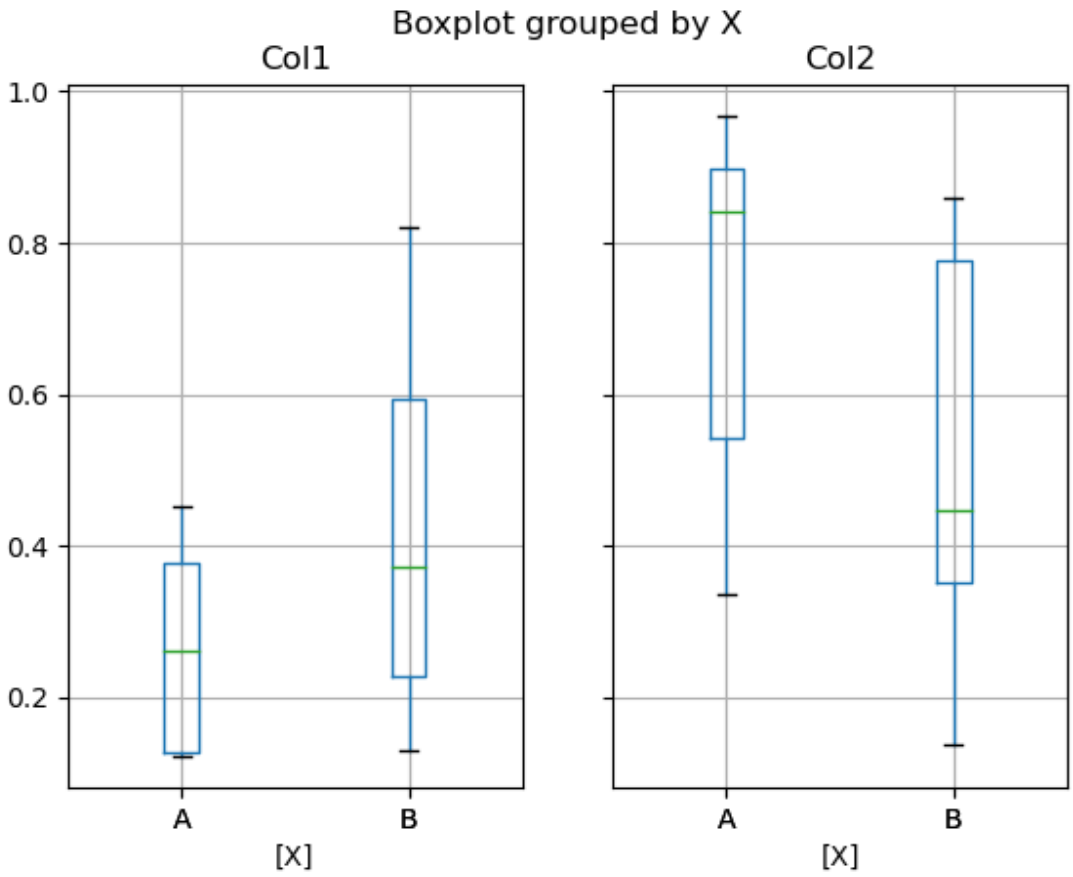
You can create a stratified boxplot using the `by` keyword argument to create groupings. For instance,

```
In [45]: df = pd.DataFrame(np.random.rand(10, 2), columns=["Col1", "Col2"])

In [46]: df["X"] = pd.Series(["A", "A", "A", "A", "A", "B", "B", "B", "B", "B"])

In [47]: plt.figure();

In [48]: bp = df.boxplot(by="X")
```



You can also pass a subset of columns to plot, as well as group by multiple columns:

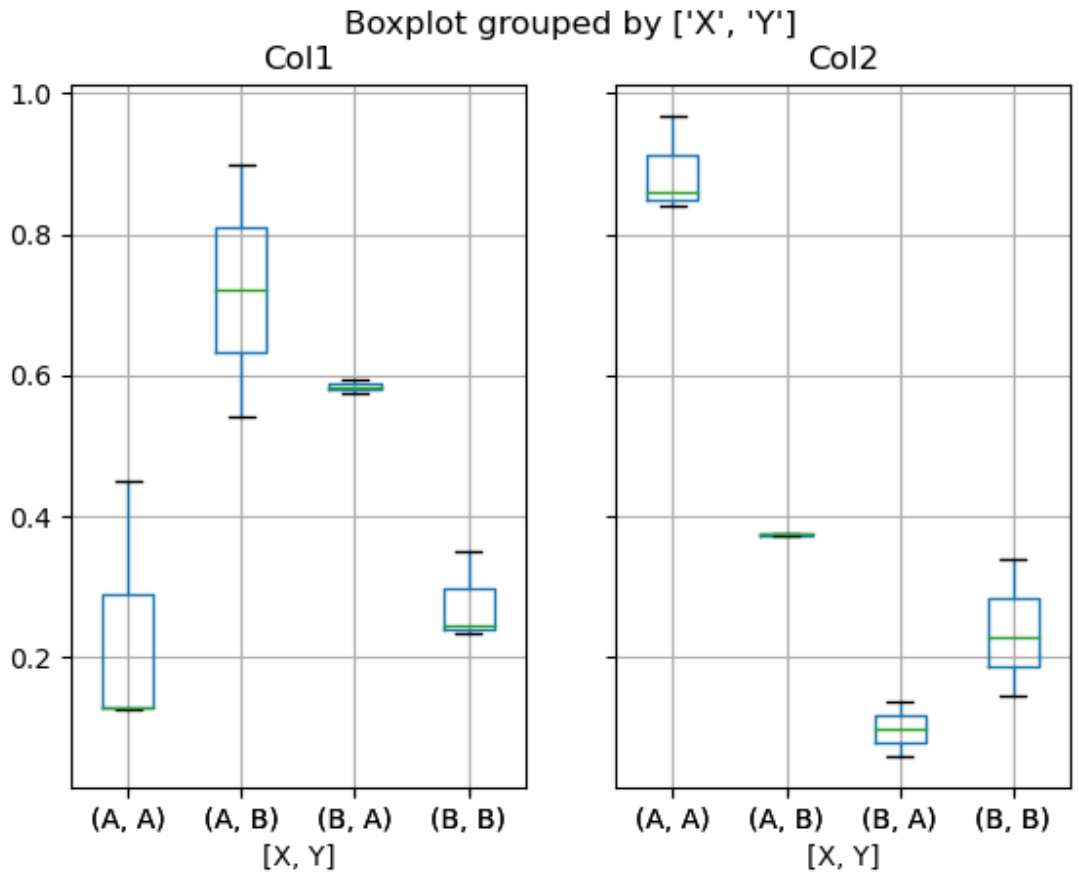
```
In [49]: df = pd.DataFrame(np.random.rand(10, 3), columns=["Col1", "Col2", "Col3"])

In [50]: df["X"] = pd.Series(["A", "A", "A", "A", "A", "B", "B", "B", "B", "B"])

In [51]: df["Y"] = pd.Series(["A", "B", "A", "B", "A", "B", "A", "B", "A", "B"])

In [52]: plt.figure();

In [53]: bp = df.boxplot(column=["Col1", "Col2"], by=["X", "Y"])
```



In `boxplot`, the return type can be controlled by the `return_type`, keyword. The valid choices are `{"axes", "dict", "both", None}`. Faceting, created by `DataFrame.boxplot` with the `by` keyword, will affect the output type as well:

`return_type`	Faceted	Output type
`None`	No	axes
`None`	Yes	2-D ndarray of axes
`'axes'`	No	axes
`'axes'`	Yes	Series of axes
`'dict'`	No	dict of artists
`'dict'`	Yes	Series of dicts of artists
`'both'`	No	namedtuple
`'both'`	Yes	Series of namedtuples

`Groupby.boxplot` always returns a `Series` of `return_type`.

```
In [54]: np.random.seed(1234)

In [55]: df_box = pd.DataFrame(np.random.randn(50, 2))

In [56]: df_box["g"] = np.random.choice(["A", "B"], size=50)

In [57]: df_box.loc[df_box["g"] == "B", 1] += 3
```

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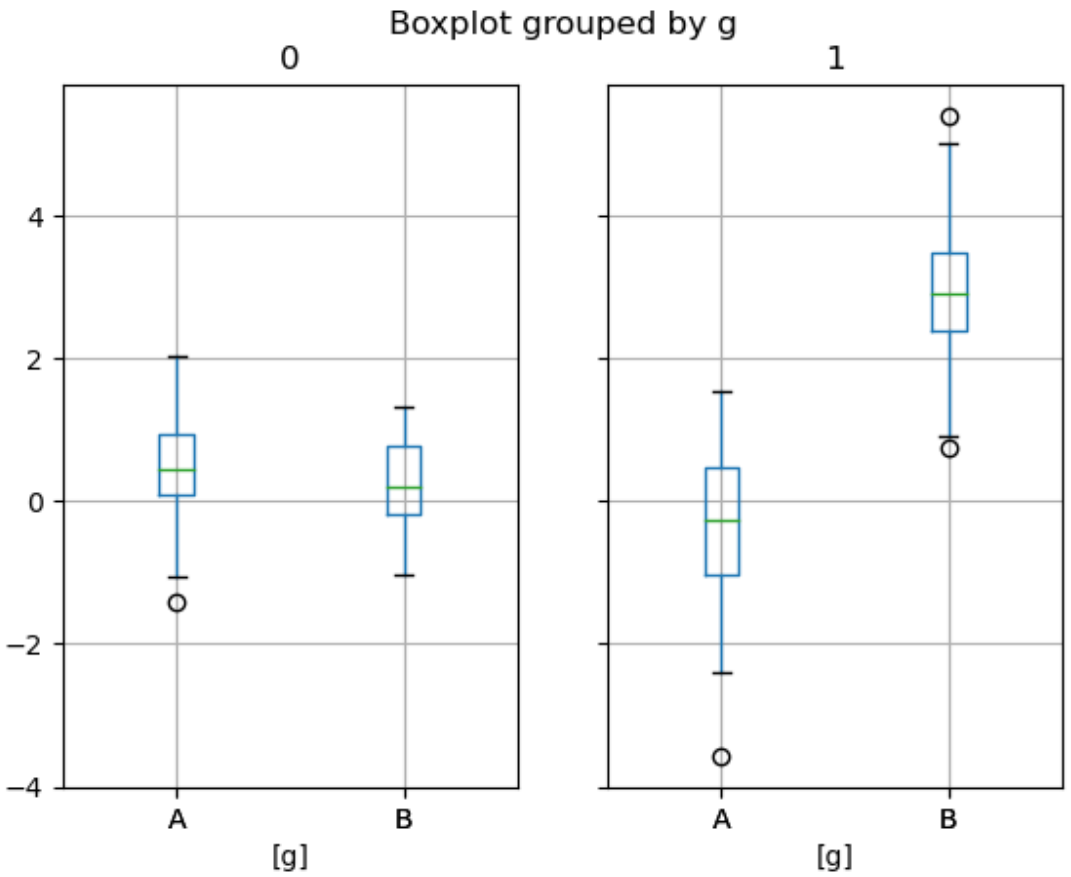
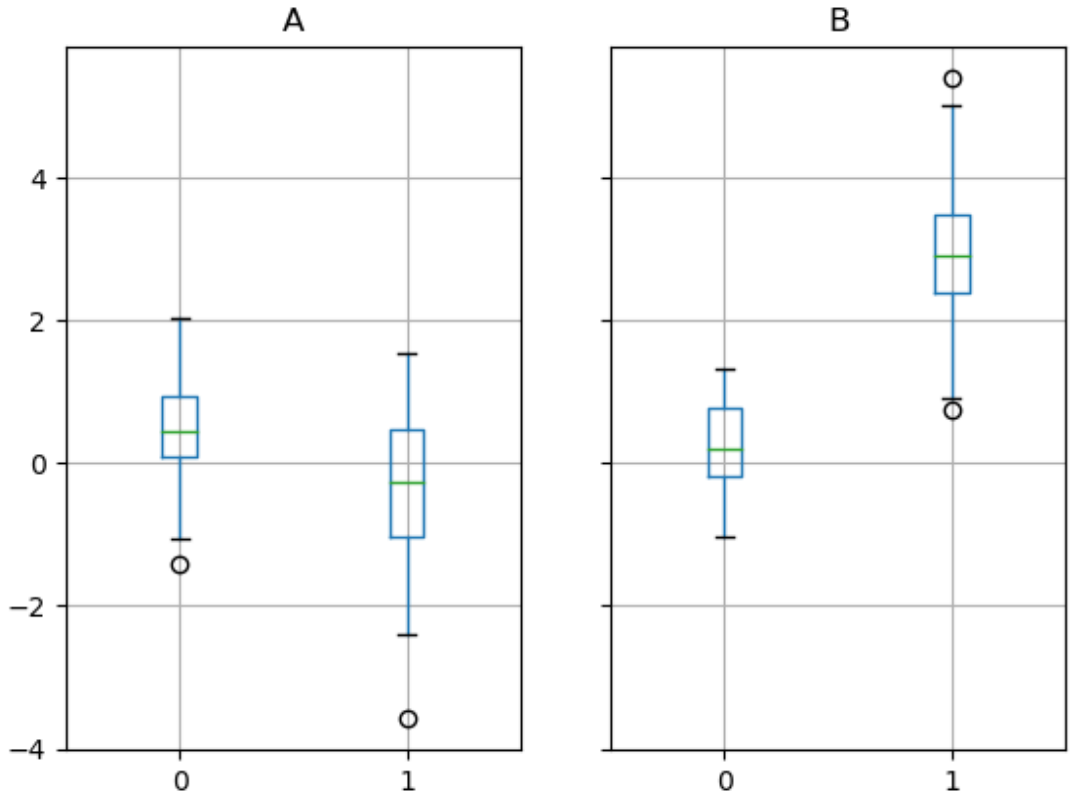
```
In [58]: bp = df_box.boxplot(by="g")
```



The subplots above are split by the numeric columns first, then the value of the g column. Below the subplots are first split by the value of g, then by the numeric columns.

```
In [59]: bp = df_box.groupby("g").boxplot()
```



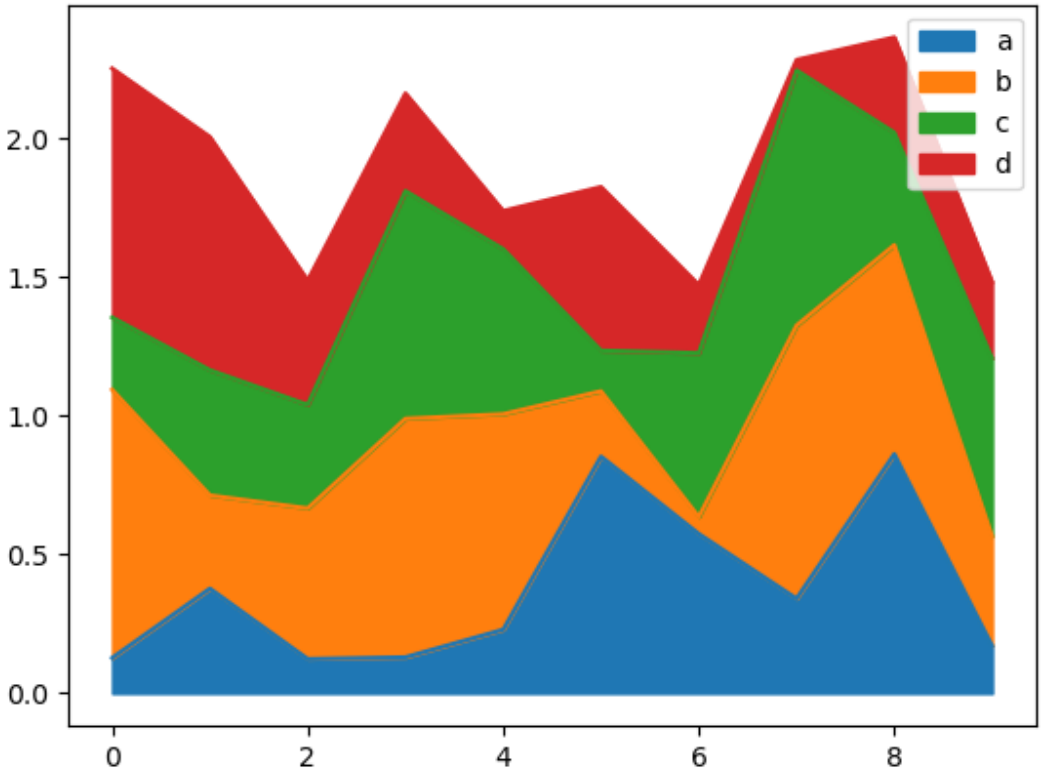
Area plot

You can create area plots with `Series.plot.area()` and `DataFrame.plot.area()`. Area plots are stacked by default. To produce stacked area plot, each column must be either all positive or all negative values.

When input data contains `NaN`, it will be automatically filled by 0. If you want to drop or fill by different values, use `dataframe.dropna()` or `dataframe.fillna()` before calling `plot`.

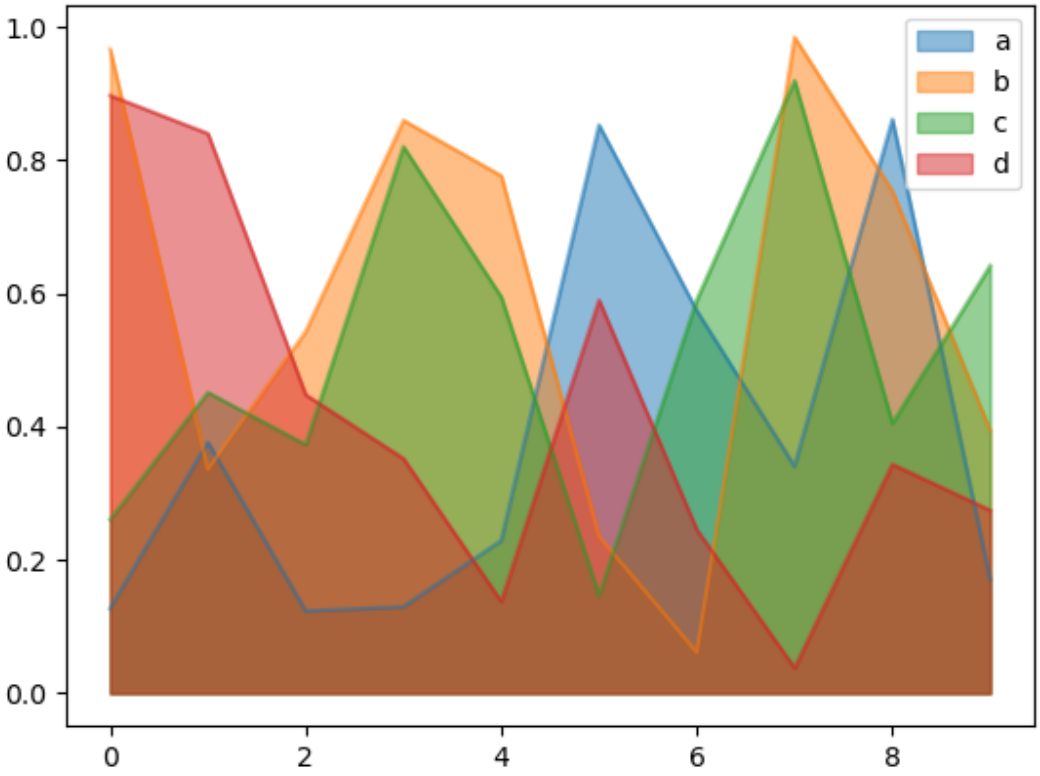
```
In [60]: df = pd.DataFrame(np.random.rand(10, 4), columns=["a", "b", "c", "d"])

In [61]: df.plot.area();
```



To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```
In [62]: df.plot.area(stacked=False);
```

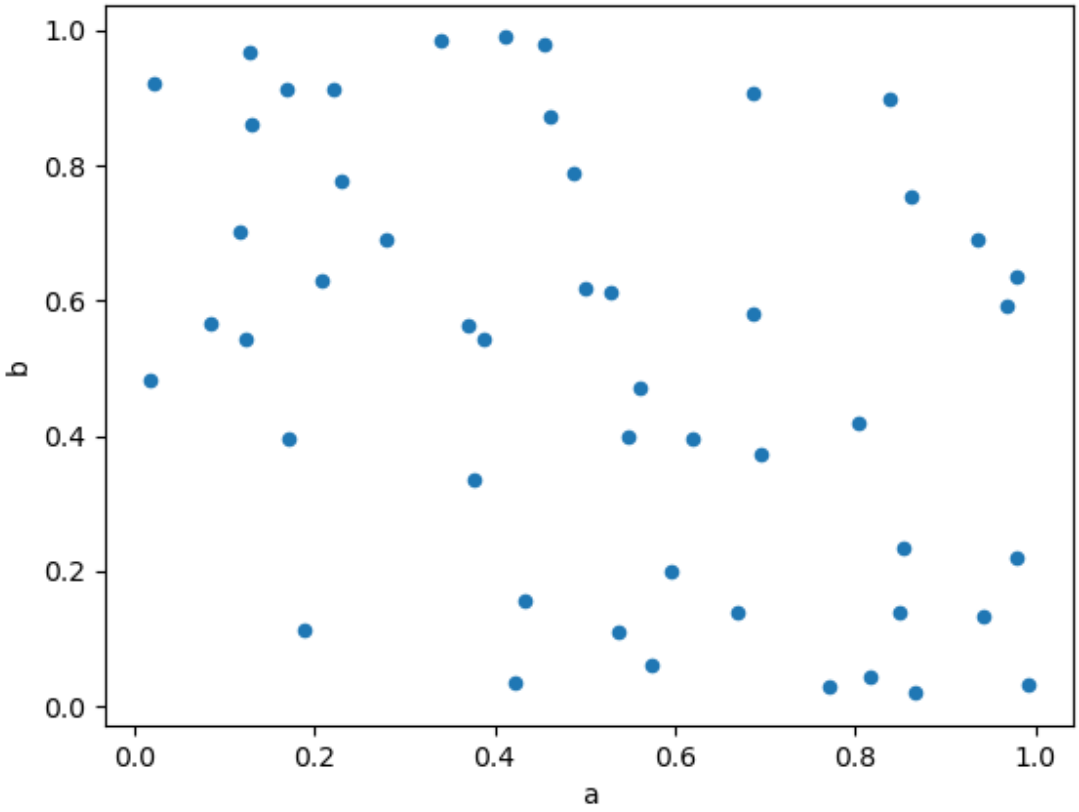


Scatter plot

Scatter plot can be drawn by using the `DataFrame.plot.scatter()` method. Scatter plot requires numeric columns for the x and y axes. These can be specified by the `x` and `y` keywords.

```
In [63]: df = pd.DataFrame(np.random.rand(50, 4), columns=["a", "b", "c", "d"])

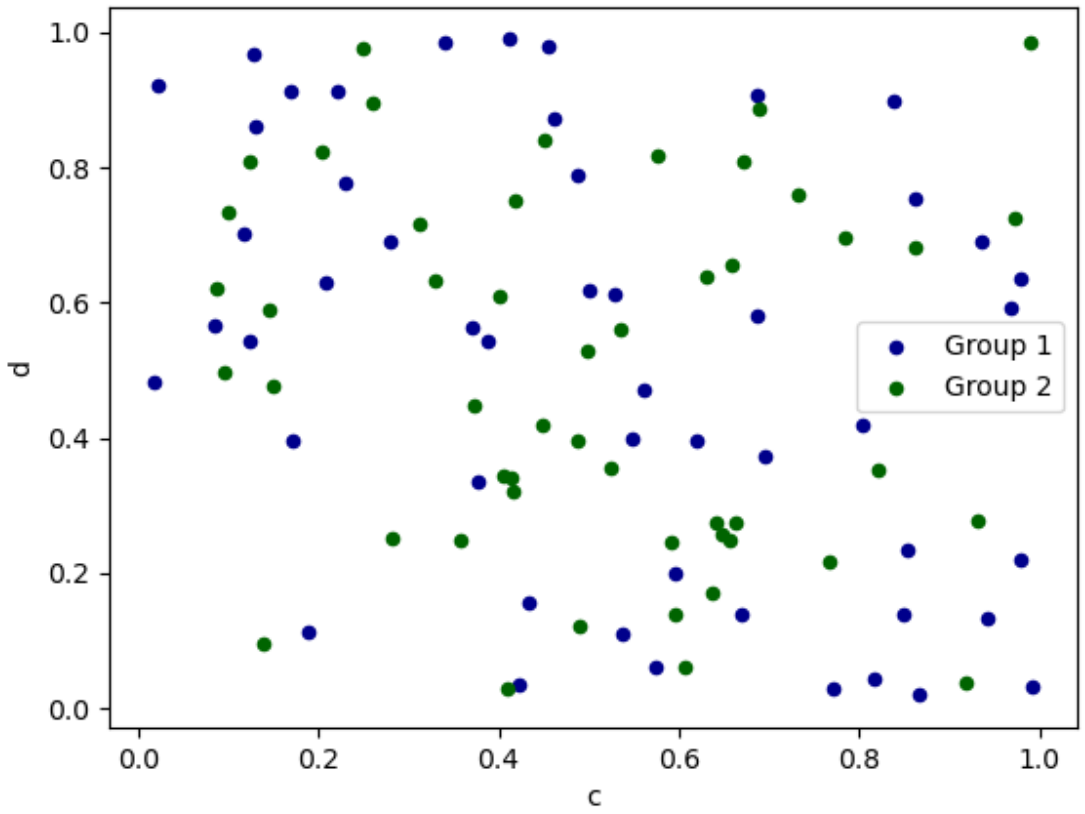
In [64]: df.plot.scatter(x="a", y="b");
```



To plot multiple column groups in a single axes, repeat `plot` method specifying target `ax`. It is recommended to specify `color` and `label` keywords to distinguish each groups.

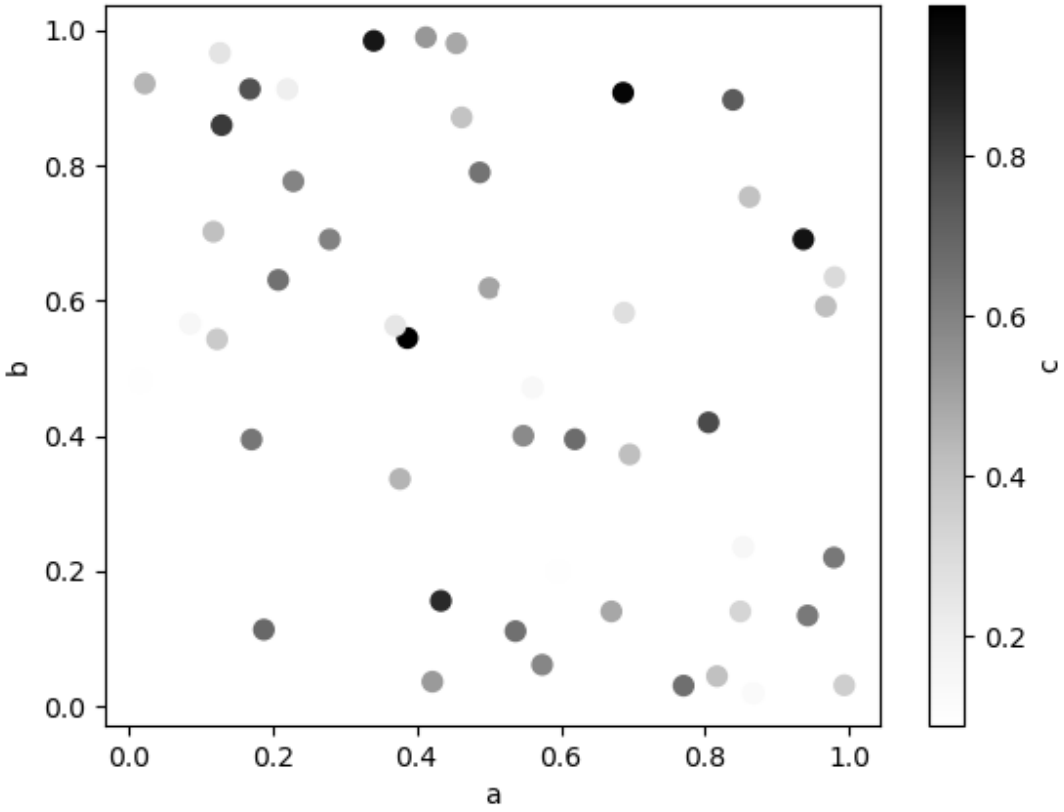
```
In [65]: ax = df.plot.scatter(x="a", y="b", color="DarkBlue", label="Group 1")

In [66]: df.plot.scatter(x="c", y="d", color="DarkGreen", label="Group 2", ax=ax);
```



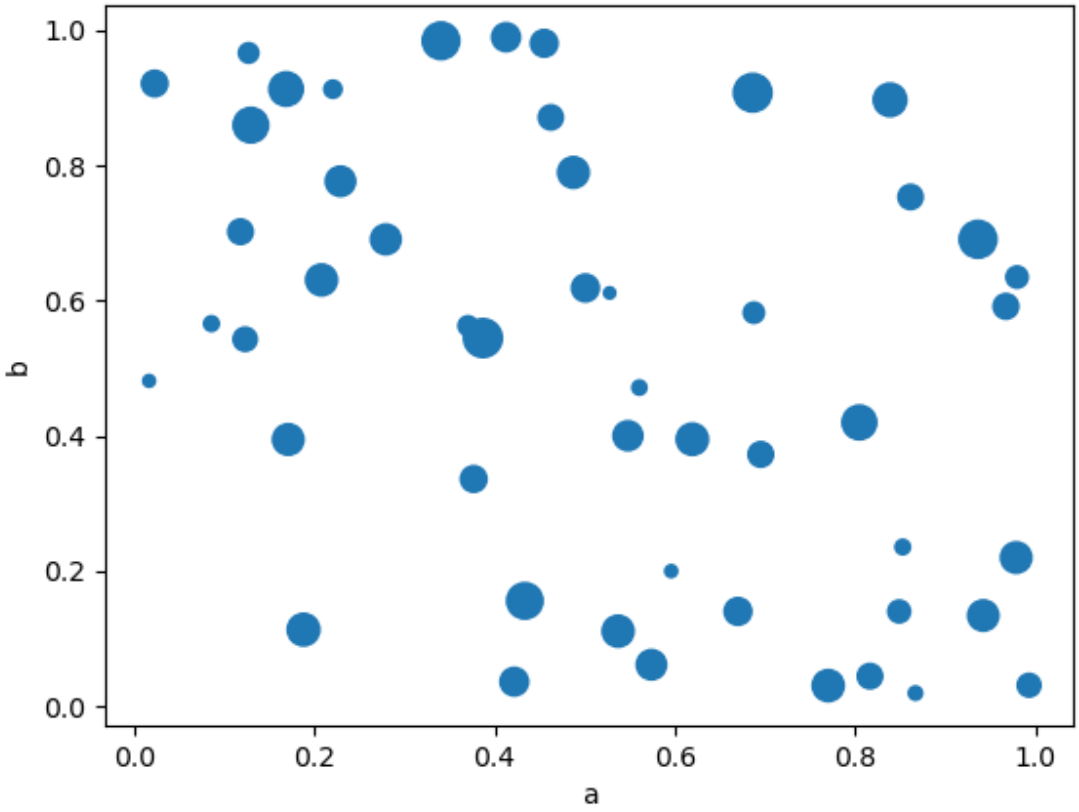
The keyword `c` may be given as the name of a column to provide colors for each point:

```
In [67]: df.plot.scatter(x="a", y="b", c="c", s=50);
```



You can pass other keywords supported by matplotlib `scatter`. The example below shows a bubble chart using a column of the `DataFrame` as the bubble size.

```
In [68]: df.plot.scatter(x="a", y="b", s=df["c"] * 200);
```



See the `scatter` method and the matplotlib scatter documentation for more.

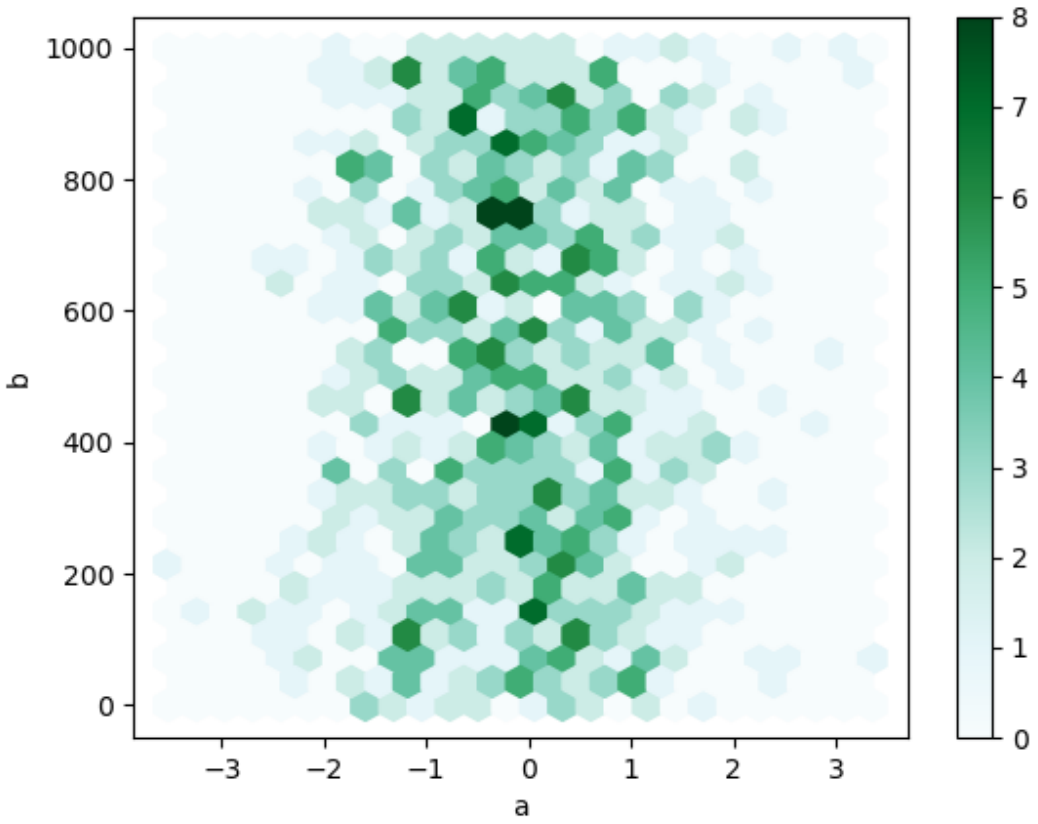
Hexagonal bin plot

You can create hexagonal bin plots with `DataFrame.plot.hexbin()`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```
In [69]: df = pd.DataFrame(np.random.randn(1000, 2), columns=["a", "b"])

In [70]: df["b"] = df["b"] + np.arange(1000)

In [71]: df.plot.hexbin(x="a", y="b", gridsize=25);
```



A useful keyword argument is `gridsize`; it controls the number of hexagons in the x-direction, and defaults to 100. A larger `gridsize` means more, smaller bins.

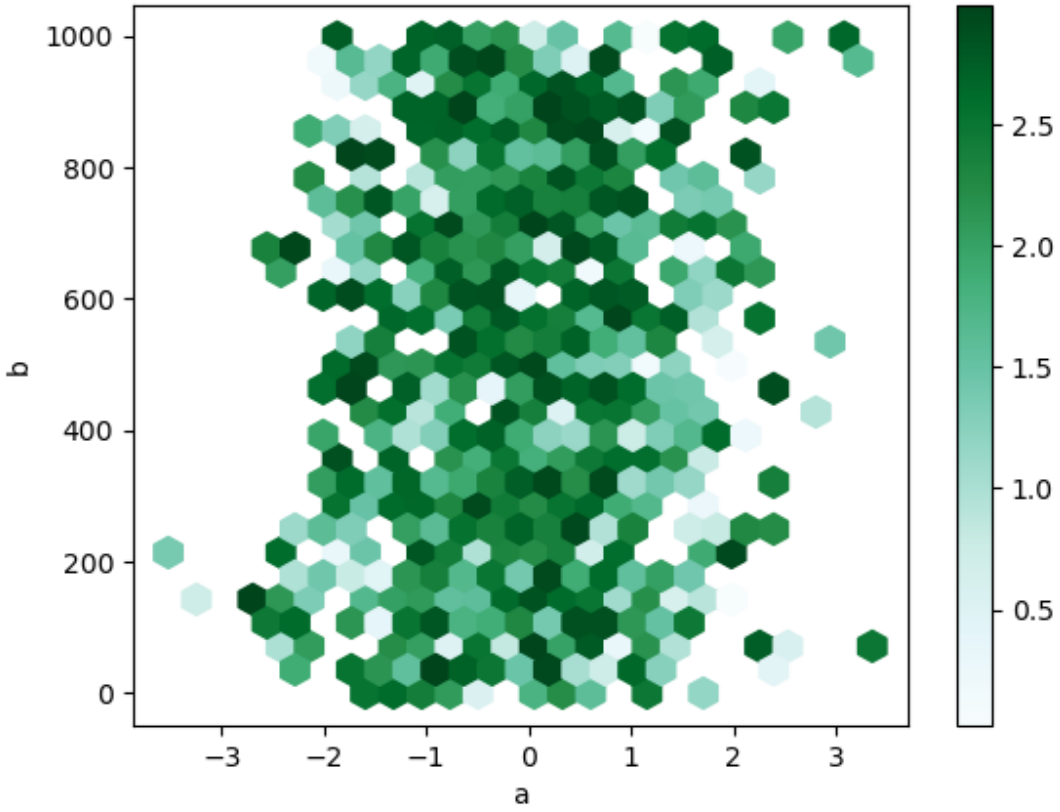
By default, a histogram of the counts around each `(x, y)` point is computed. You can specify alternative aggregations by passing values to the `C` and `reduce_C_function` arguments. `C` specifies the value at each `(x, y)` point and `reduce_C_function` is a function of one argument that reduces all the values in a bin to a single number (e.g. `mean`, `max`, `sum`, `std`). In this example the positions are given by columns `a` and `b`, while the value is given by column `z`. The bins are aggregated with NumPy's `max` function.

```
In [72]: df = pd.DataFrame(np.random.randn(1000, 2), columns=["a", "b"])

In [73]: df["b"] = df["b"] = df["b"] + np.arange(1000)

In [74]: df["z"] = np.random.uniform(0, 3, 1000)

In [75]: df.plot.hexbin(x="a", y="b", C="z", reduce_C_function=np.max, gridsize=25);
```



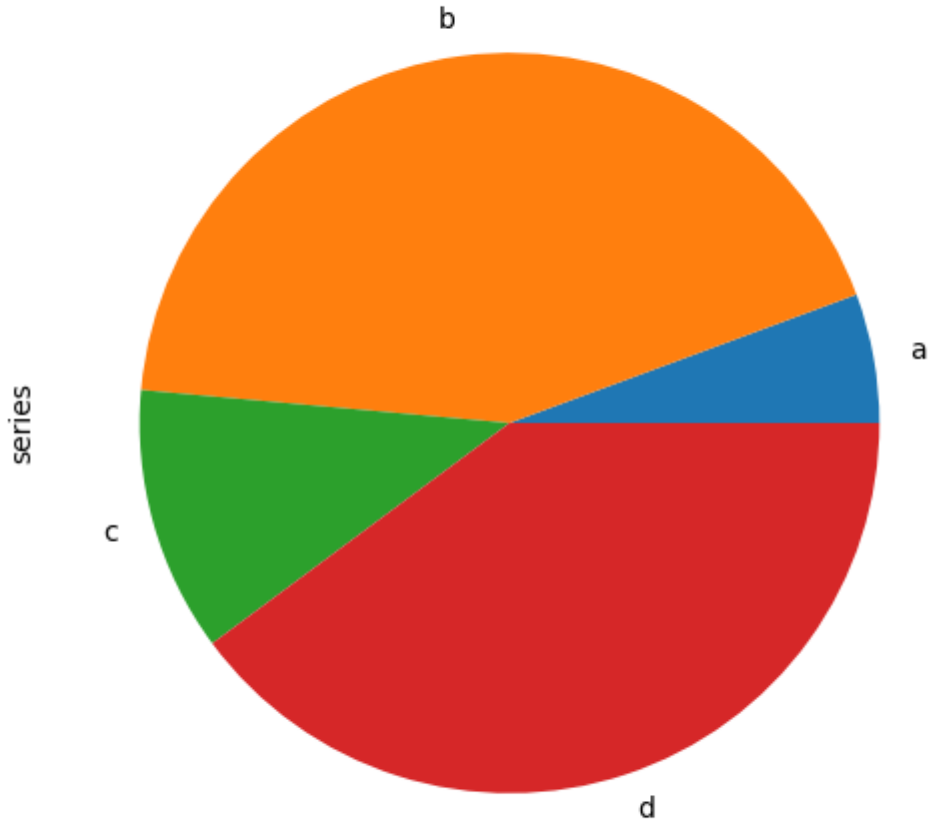
See the `hexbin` method and the matplotlib hexbin documentation for more.

Pie plot

You can create a pie plot with `DataFrame.plot.pie()` or `Series.plot.pie()`. If your data includes any `NaN`, they will be automatically filled with 0. A `ValueError` will be raised if there are any negative values in your data.

```
In [76]: series = pd.Series(3 * np.random.rand(4), index=["a", "b", "c", "d"], name=
↪"series")

In [77]: series.plot.pie(figsize=(6, 6));
```

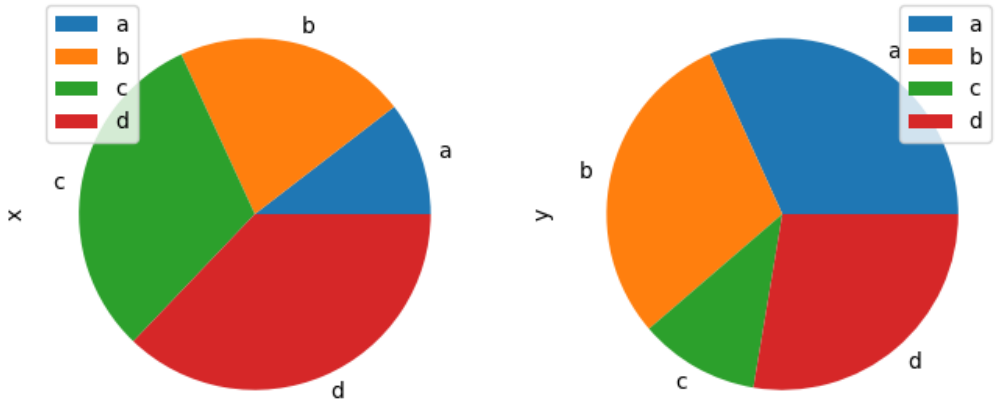


For pie plots it's best to use square figures, i.e. a figure aspect ratio 1. You can create the figure with equal width and height, or force the aspect ratio to be equal after plotting by calling `ax.set_aspect('equal')` on the returned `axes` object.

Note that pie plot with `DataFrame` requires that you either specify a target column by the `y` argument or `subplots=True`. When `y` is specified, pie plot of selected column will be drawn. If `subplots=True` is specified, pie plots for each column are drawn as subplots. A legend will be drawn in each pie plots by default; specify `legend=False` to hide it.

```
In [78]: df = pd.DataFrame(
   ....:     3 * np.random.rand(4, 2), index=["a", "b", "c", "d"], columns=["x", "y"]
   ....: )
   ....:

In [79]: df.plot.pie(subplots=True, figsize=(8, 4));
```

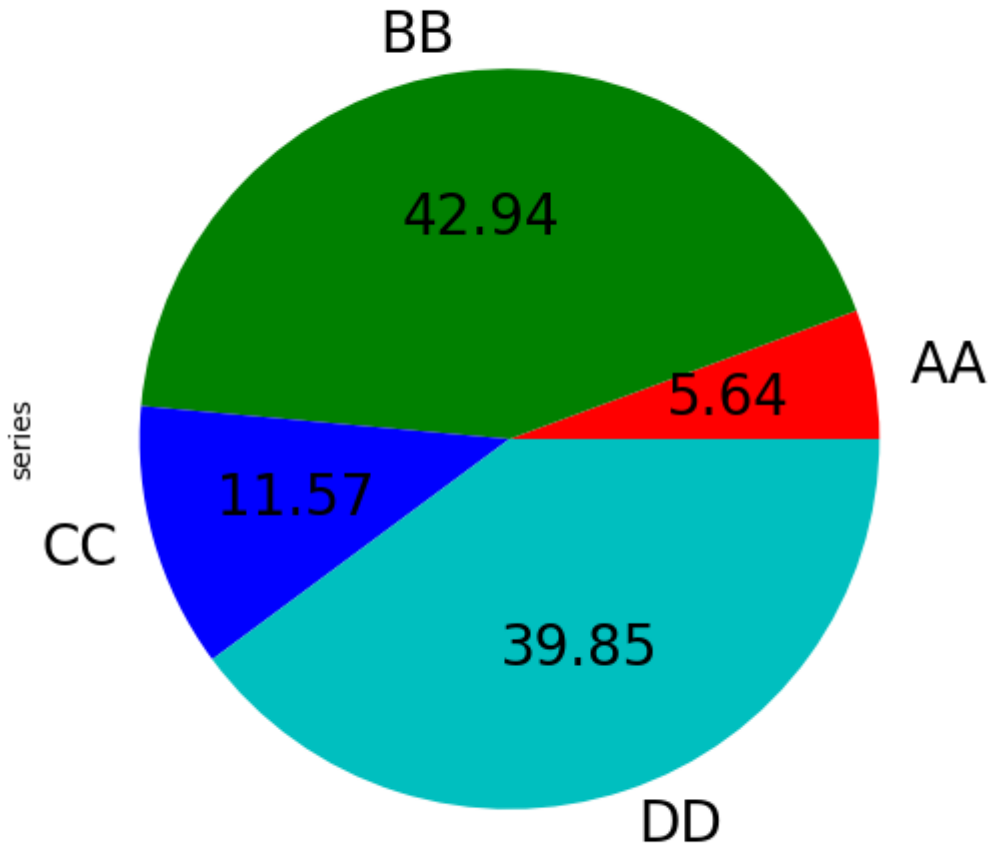


You can use the `labels` and `colors` keywords to specify the labels and colors of each wedge.

Warning: Most pandas plots use the `label` and `color` arguments (note the lack of "s" on those). To be consistent with `matplotlib.pyplot.pie()` you must use `labels` and `colors`.

If you want to hide wedge labels, specify `labels=None`. If `fontsize` is specified, the value will be applied to wedge labels. Also, other keywords supported by `matplotlib.pyplot.pie()` can be used.

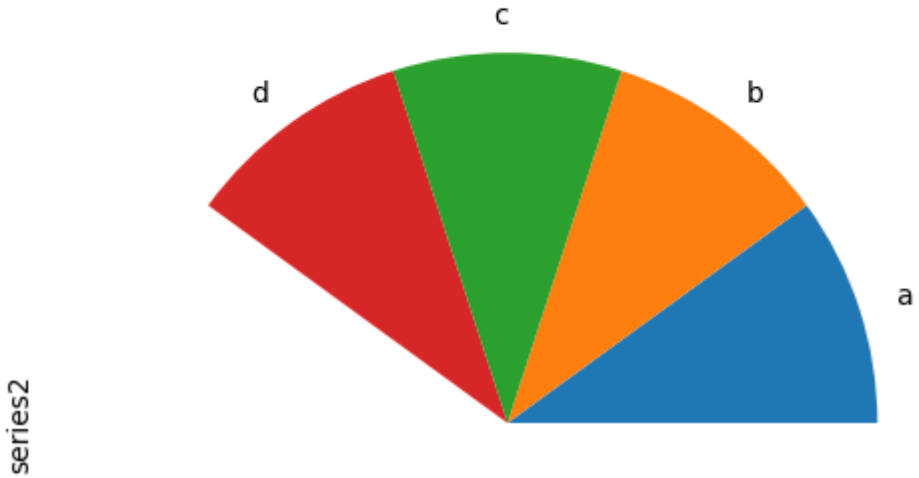
```
In [80]: series.plot.pie(
   ....:     labels=["AA", "BB", "CC", "DD"],
   ....:     colors=["r", "g", "b", "c"],
   ....:     autopct="%.2f",
   ....:     fontsize=20,
   ....:     figsize=(6, 6),
   ....: );
   ....:
```



If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```
In [81]: series = pd.Series([0.1] * 4, index=["a", "b", "c", "d"], name="series2")

In [82]: series.plot.pie(figsize=(6, 6));
```



See the matplotlib pie documentation for more.

2.15.3 Plotting with missing data

pandas tries to be pragmatic about plotting `DataFrames` or `Series` that contain missing data. Missing values are dropped, left out, or filled depending on the plot type.

Plot Type	NaN Handling
Line	Leave gaps at NaNs
Line (stacked)	Fill 0's
Bar	Fill 0's
Scatter	Drop NaNs
Histogram	Drop NaNs (column-wise)
Box	Drop NaNs (column-wise)
Area	Fill 0's
KDE	Drop NaNs (column-wise)
Hexbin	Drop NaNs
Pie	Fill 0's

If any of these defaults are not what you want, or if you want to be explicit about how missing values are handled, consider using *fillna()* or *dropna()* before plotting.

2.15.4 Plotting tools

These functions can be imported from `pandas.plotting` and take a `Series` or `DataFrame` as an argument.

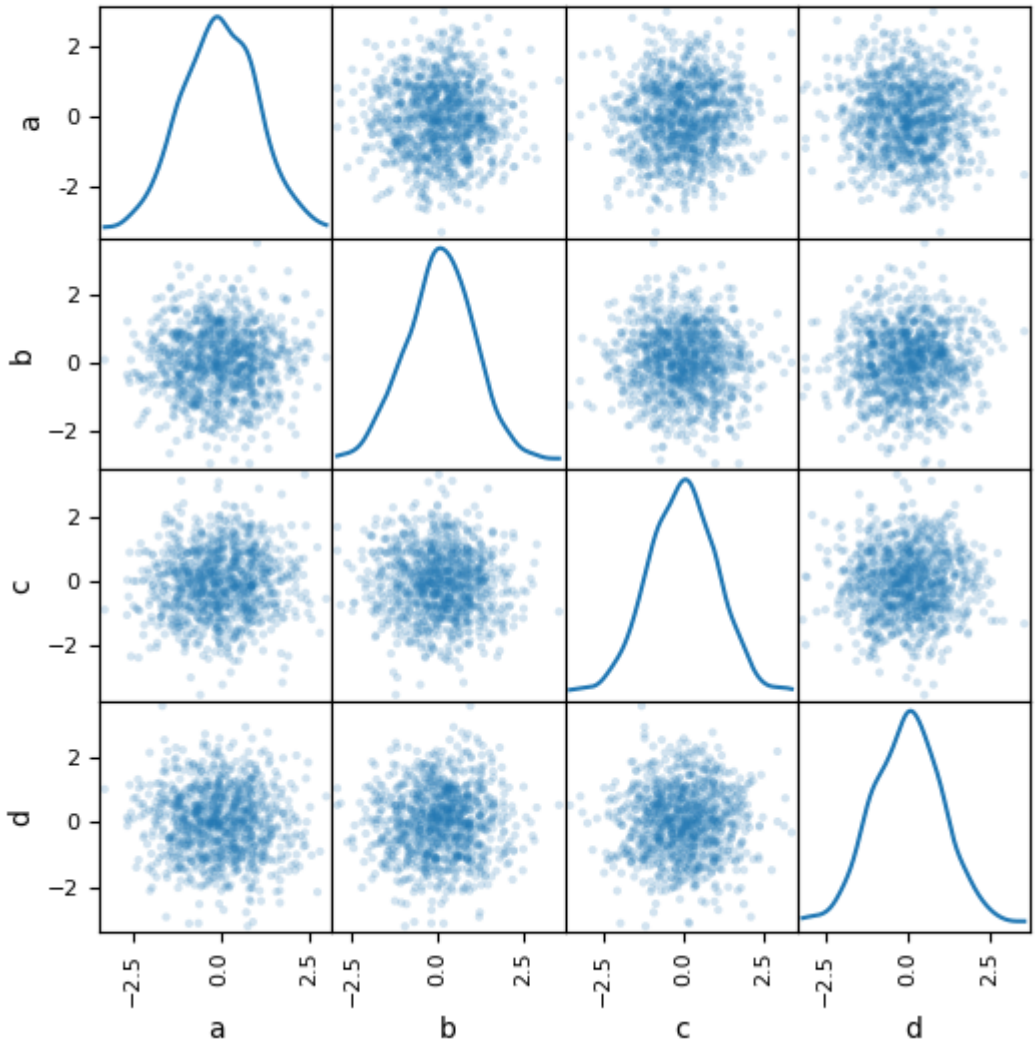
Scatter matrix plot

You can create a scatter plot matrix using the `scatter_matrix` method in `pandas.plotting`:

```
In [83]: from pandas.plotting import scatter_matrix

In [84]: df = pd.DataFrame(np.random.randn(1000, 4), columns=["a", "b", "c", "d"])

In [85]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal="kde");
```

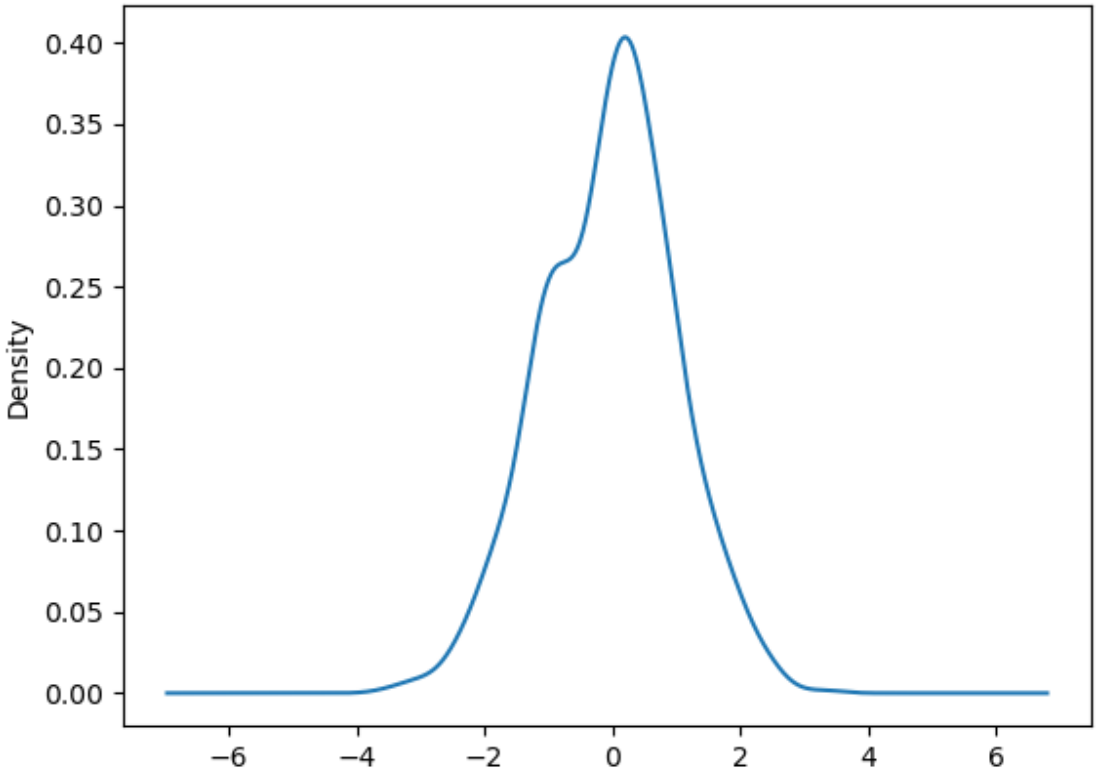


Density plot

You can create density plots using the `Series.plot.kde()` and `DataFrame.plot.kde()` methods.

```
In [86]: ser = pd.Series(np.random.randn(1000))

In [87]: ser.plot.kde();
```



Andrews curves

Andrews curves allow one to plot multivariate data as a large number of curves that are created using the attributes of samples as coefficients for Fourier series, see the Wikipedia entry for more information. By coloring these curves differently for each class it is possible to visualize data clustering. Curves belonging to samples of the same class will usually be closer together and form larger structures.

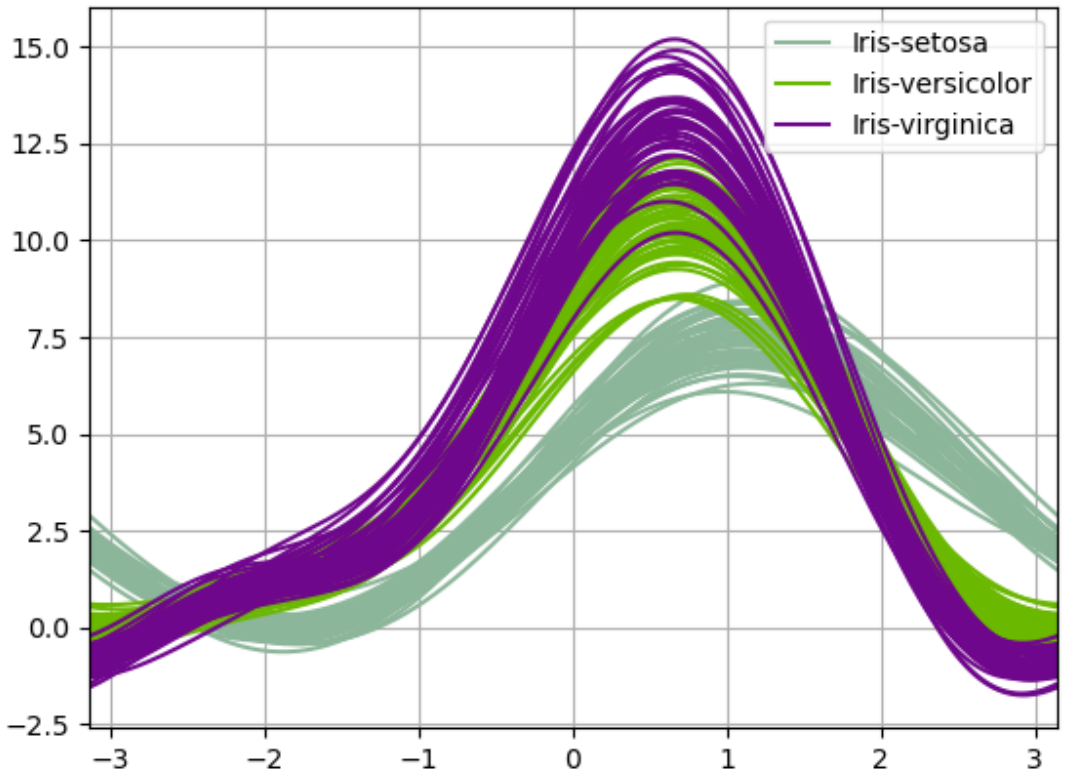
Note: The "Iris" dataset is available here.

```
In [88]: from pandas.plotting import andrews_curves

In [89]: data = pd.read_csv("data/iris.data")

In [90]: plt.figure();

In [91]: andrews_curves(data, "Name");
```



Parallel coordinates

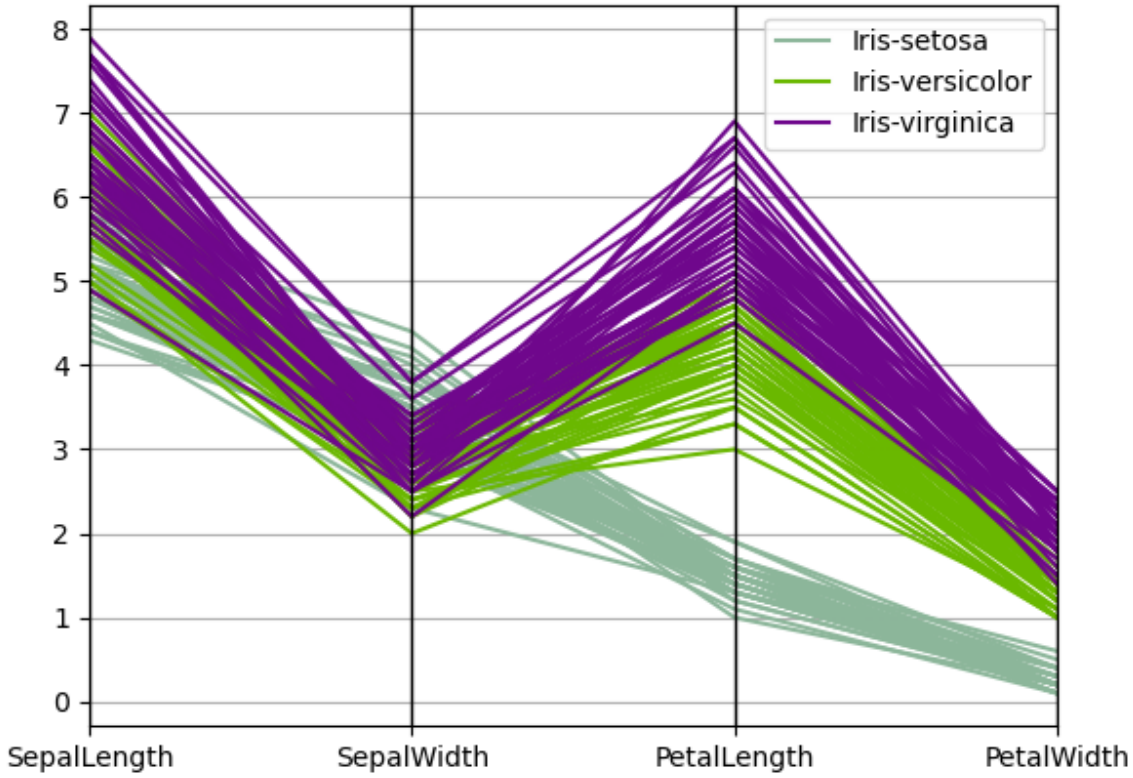
Parallel coordinates is a plotting technique for plotting multivariate data, see the Wikipedia entry for an introduction. Parallel coordinates allows one to see clusters in data and to estimate other statistics visually. Using parallel coordinates points are represented as connected line segments. Each vertical line represents one attribute. One set of connected line segments represents one data point. Points that tend to cluster will appear closer together.

```
In [92]: from pandas.plotting import parallel_coordinates

In [93]: data = pd.read_csv("data/iris.data")

In [94]: plt.figure();

In [95]: parallel_coordinates(data, "Name");
```



Lag plot

Lag plots are used to check if a data set or time series is random. Random data should not exhibit any structure in the lag plot. Non-random structure implies that the underlying data are not random. The `lag` argument may be passed, and when `lag=1` the plot is essentially `data[:-1]` vs. `data[1:]`.

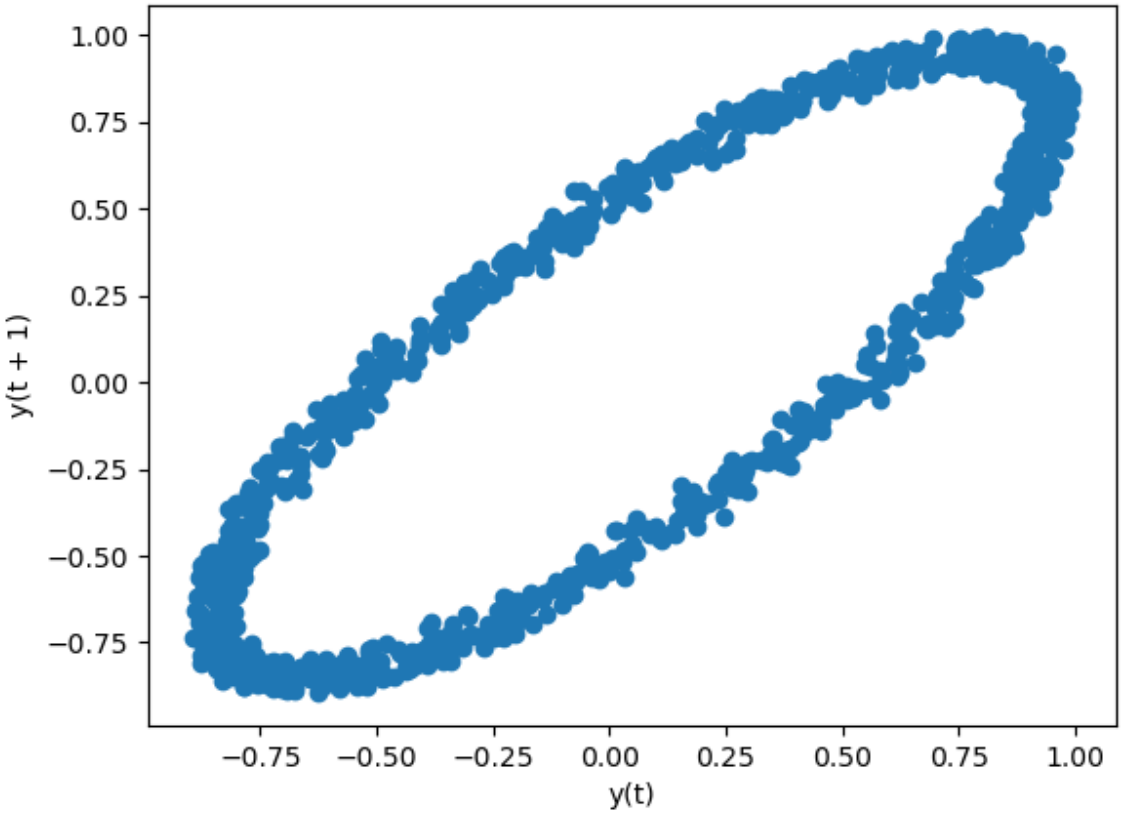
```
In [96]: from pandas.plotting import lag_plot

In [97]: plt.figure();

In [98]: spacing = np.linspace(-99 * np.pi, 99 * np.pi, num=1000)

In [99]: data = pd.Series(0.1 * np.random.rand(1000) + 0.9 * np.sin(spacing))

In [100]: lag_plot(data);
```



Autocorrelation plot

Autocorrelation plots are often used for checking randomness in time series. This is done by computing autocorrelations for data values at varying time lags. If time series is random, such autocorrelations should be near zero for any and all time-lag separations. If time series is non-random then one or more of the autocorrelations will be significantly non-zero. The horizontal lines displayed in the plot correspond to 95% and 99% confidence bands. The dashed line is 99% confidence band. See the Wikipedia entry for more about autocorrelation plots.

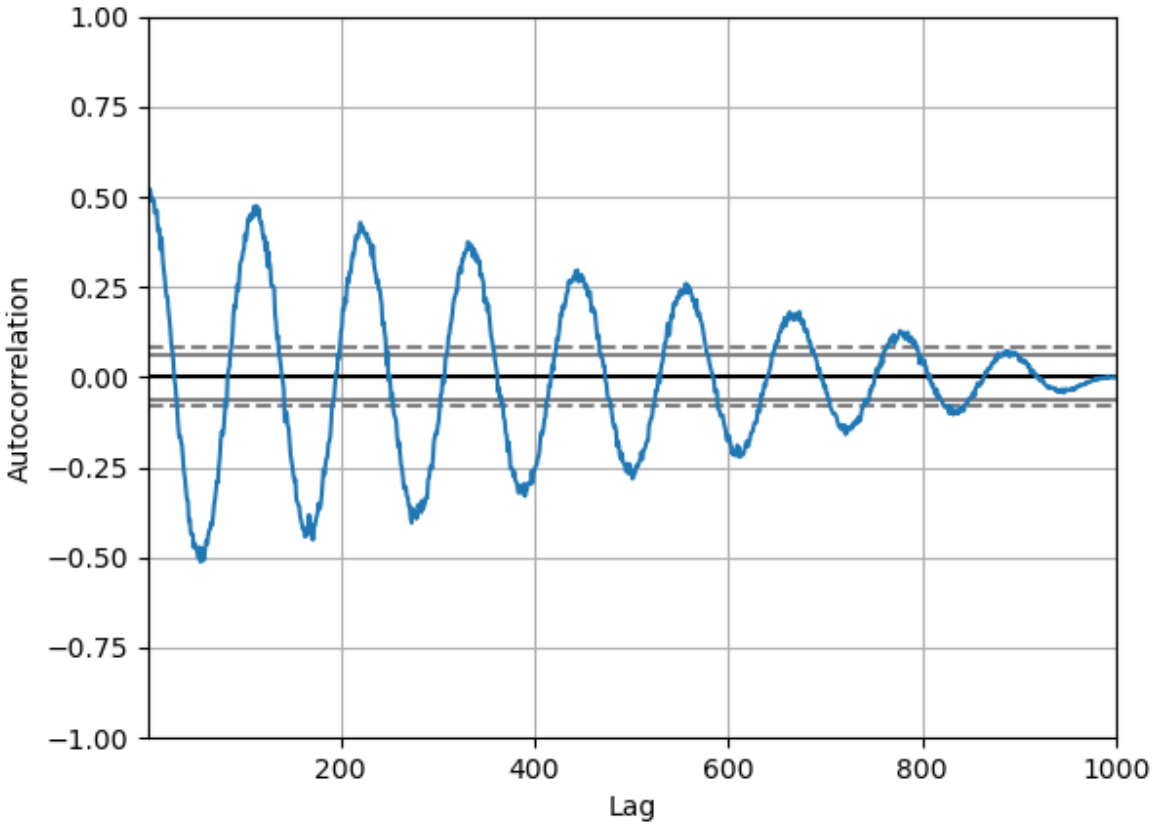
```
In [101]: from pandas.plotting import autocorrelation_plot

In [102]: plt.figure();

In [103]: spacing = np.linspace(-9 * np.pi, 9 * np.pi, num=1000)

In [104]: data = pd.Series(0.7 * np.random.rand(1000) + 0.3 * np.sin(spacing))

In [105]: autocorrelation_plot(data);
```



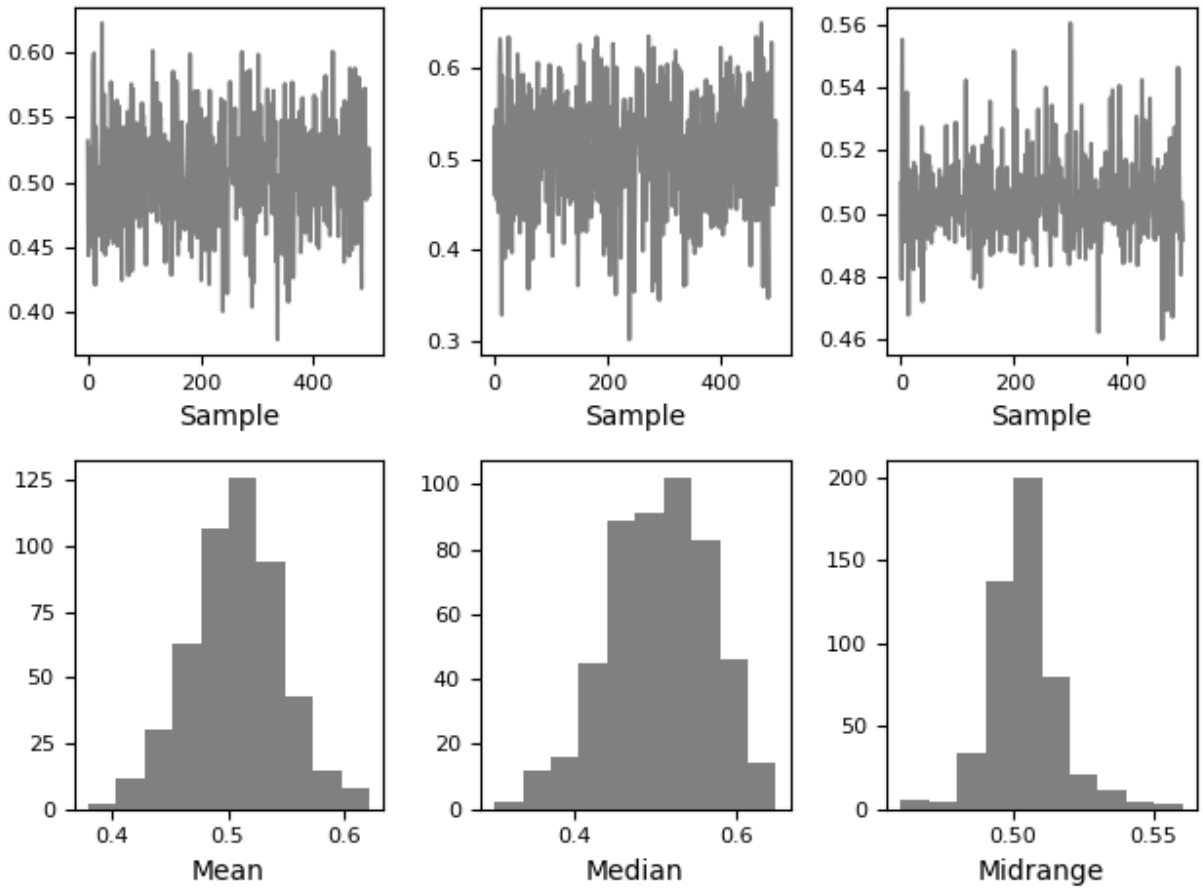
Bootstrap plot

Bootstrap plots are used to visually assess the uncertainty of a statistic, such as mean, median, midrange, etc. A random subset of a specified size is selected from a data set, the statistic in question is computed for this subset and the process is repeated a specified number of times. Resulting plots and histograms are what constitutes the bootstrap plot.

```
In [106]: from pandas.plotting import bootstrap_plot

In [107]: data = pd.Series(np.random.rand(1000))

In [108]: bootstrap_plot(data, size=50, samples=500, color="grey");
```



RadViz

RadViz is a way of visualizing multi-variate data. It is based on a simple spring tension minimization algorithm. Basically you set up a bunch of points in a plane. In our case they are equally spaced on a unit circle. Each point represents a single attribute. You then pretend that each sample in the data set is attached to each of these points by a spring, the stiffness of which is proportional to the numerical value of that attribute (they are normalized to unit interval). The point in the plane, where our sample settles to (where the forces acting on our sample are at an equilibrium) is where a dot representing our sample will be drawn. Depending on which class that sample belongs it will be colored differently. See the R package Radviz for more information.

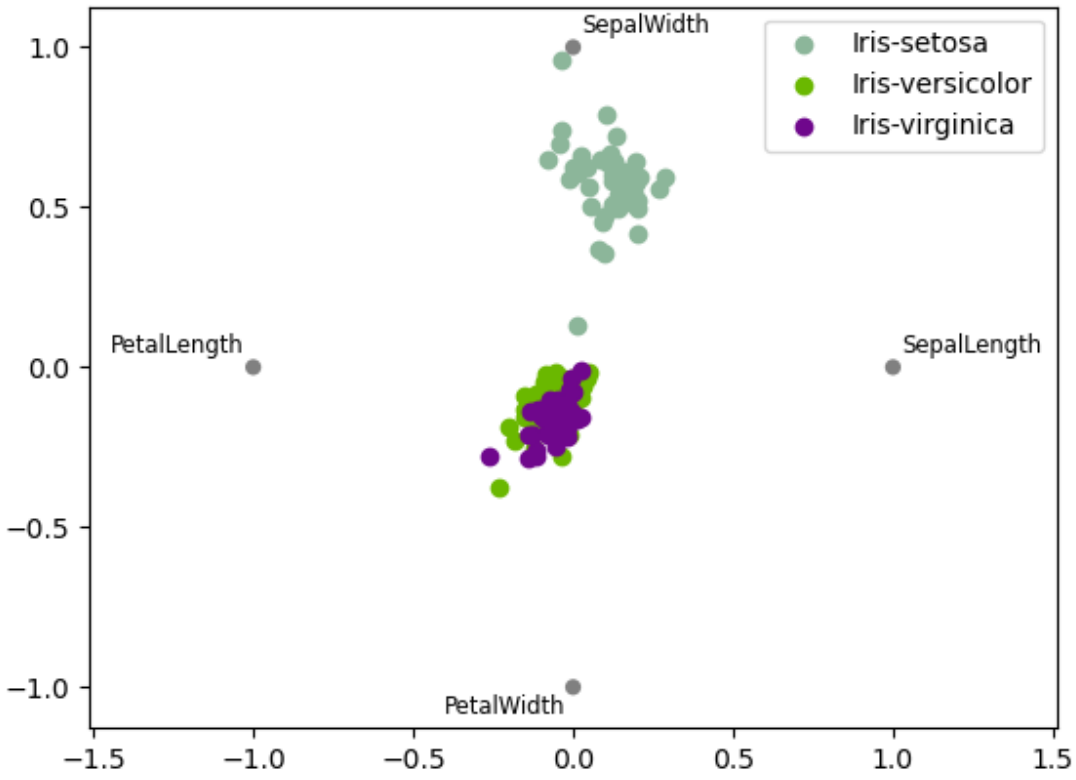
Note: The "Iris" dataset is available here.

```
In [109]: from pandas.plotting import radviz

In [110]: data = pd.read_csv("data/iris.data")

In [111]: plt.figure();

In [112]: radviz(data, "Name");
```



2.15.5 Plot formatting

Setting the plot style

From version 1.5 and up, matplotlib offers a range of pre-configured plotting styles. Setting the style can be used to easily give plots the general look that you want. Setting the style is as easy as calling `matplotlib.style.use(my_plot_style)` before creating your plot. For example you could write `matplotlib.style.use('ggplot')` for ggplot-style plots.

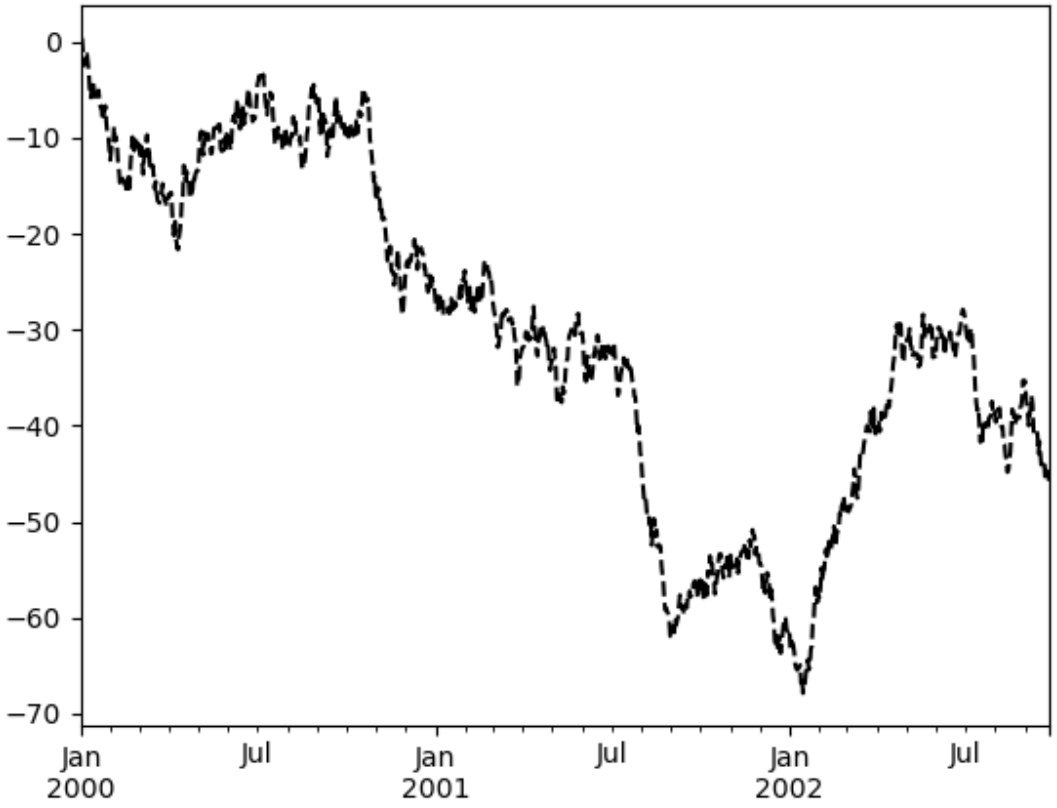
You can see the various available style names at `matplotlib.style.available` and it's very easy to try them out.

General plot style arguments

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```
In [113]: plt.figure();

In [114]: ts.plot(style="k--", label="Series");
```



For each kind of plot (e.g. `line`, `bar`, `scatter`) any additional arguments keywords are passed along to the corresponding matplotlib function (`ax.plot()`, `ax.bar()`, `ax.scatter()`). These can be used to control additional styling, beyond what pandas provides.

Controlling the legend

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```
In [115]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list(
↪"ABCD"))

In [116]: df = df.cumsum()

In [117]: df.plot(legend=False);
```

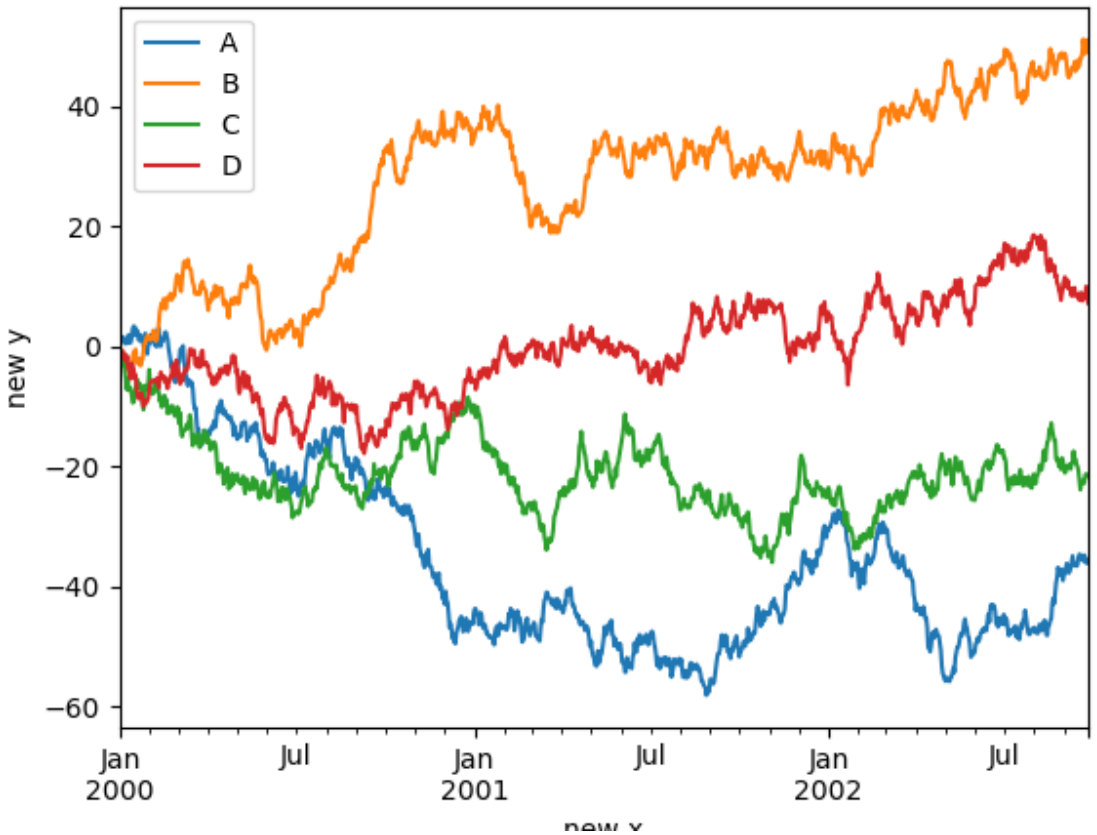
Controlling the labels

New in version 1.1.0.

You may set the `xlabel` and `ylabel` arguments to give the plot custom labels for x and y axis. By default, pandas will pick up index name as xlabel, while leaving it empty for ylabel.

```
In [118]: df.plot();

In [119]: df.plot(xlabel="new x", ylabel="new y");
```



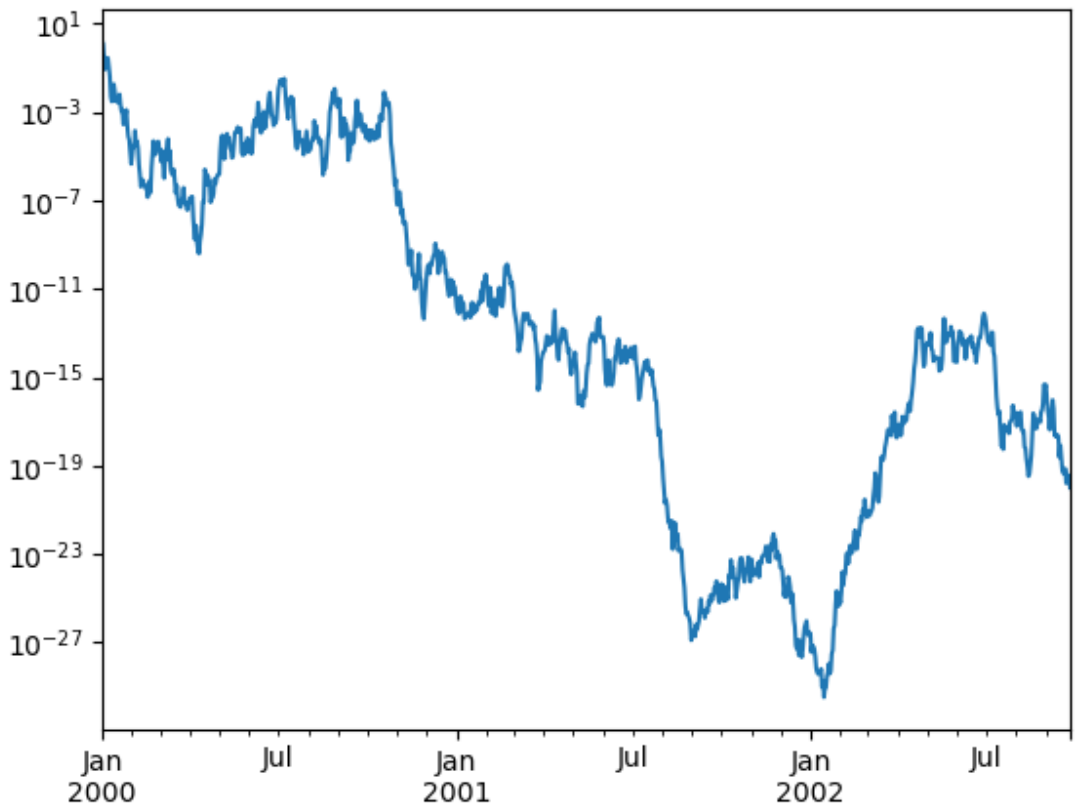
Scales

You may pass `logy` to get a log-scale Y axis.

```
In [120]: ts = pd.Series(np.random.randn(1000), index=pd.date_range("1/1/2000",␣
↪periods=1000))

In [121]: ts = np.exp(ts.cumsum())

In [122]: ts.plot(logy=True);
```



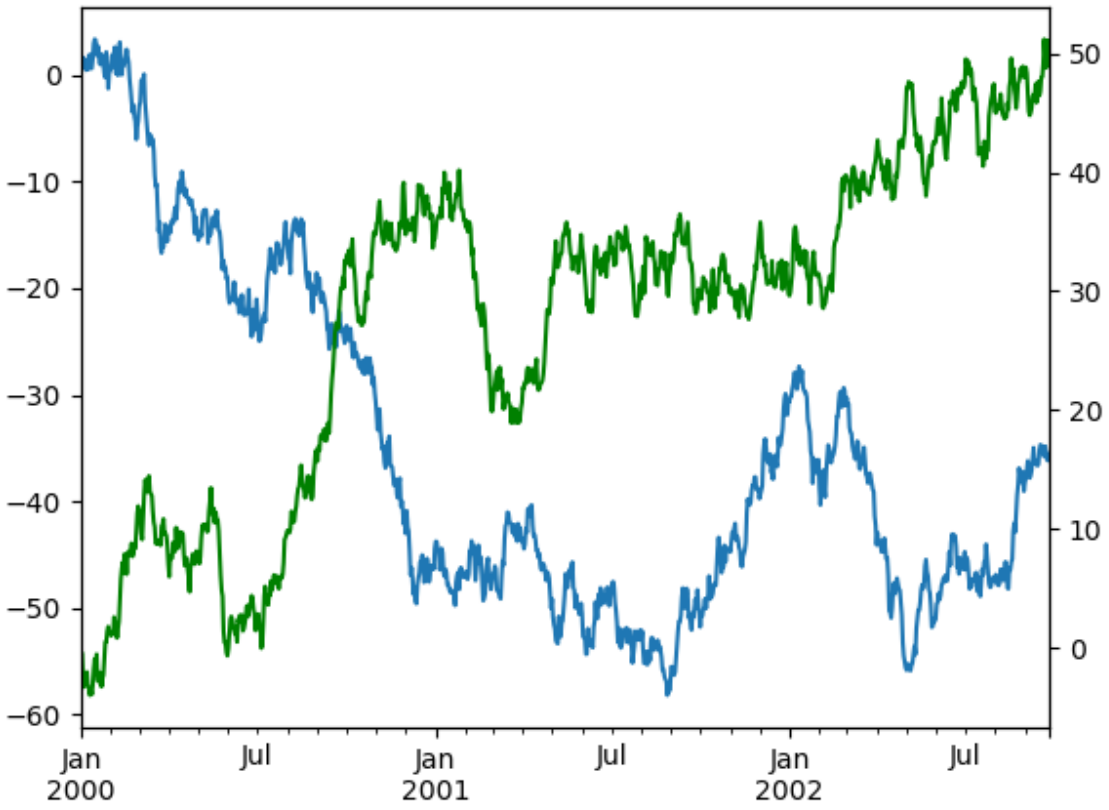
See also the `logx` and `loglog` keyword arguments.

Plotting on a secondary y-axis

To plot data on a secondary y-axis, use the `secondary_y` keyword:

```
In [123]: df["A"].plot();

In [124]: df["B"].plot(secondary_y=True, style="g");
```



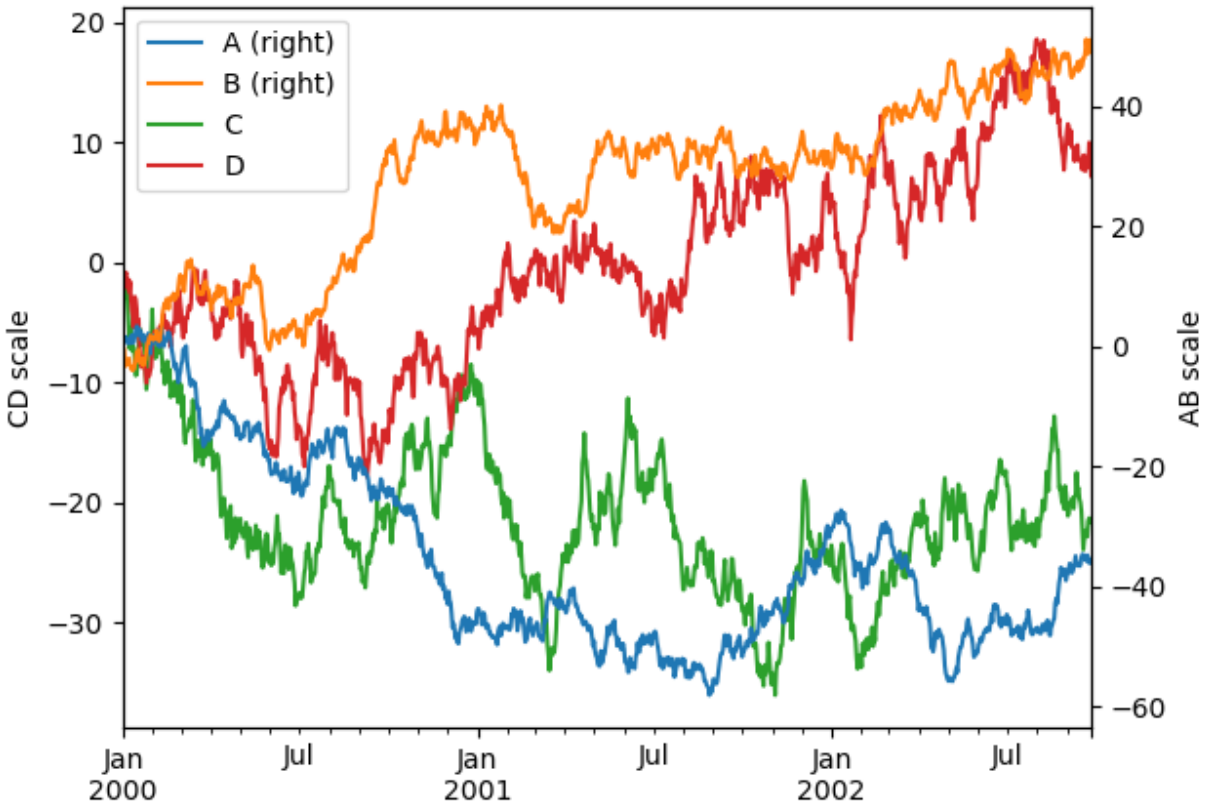
To plot some columns in a `DataFrame`, give the column names to the `secondary_y` keyword:

```
In [125]: plt.figure();

In [126]: ax = df.plot(secondary_y=["A", "B"])

In [127]: ax.set_ylabel("CD scale");

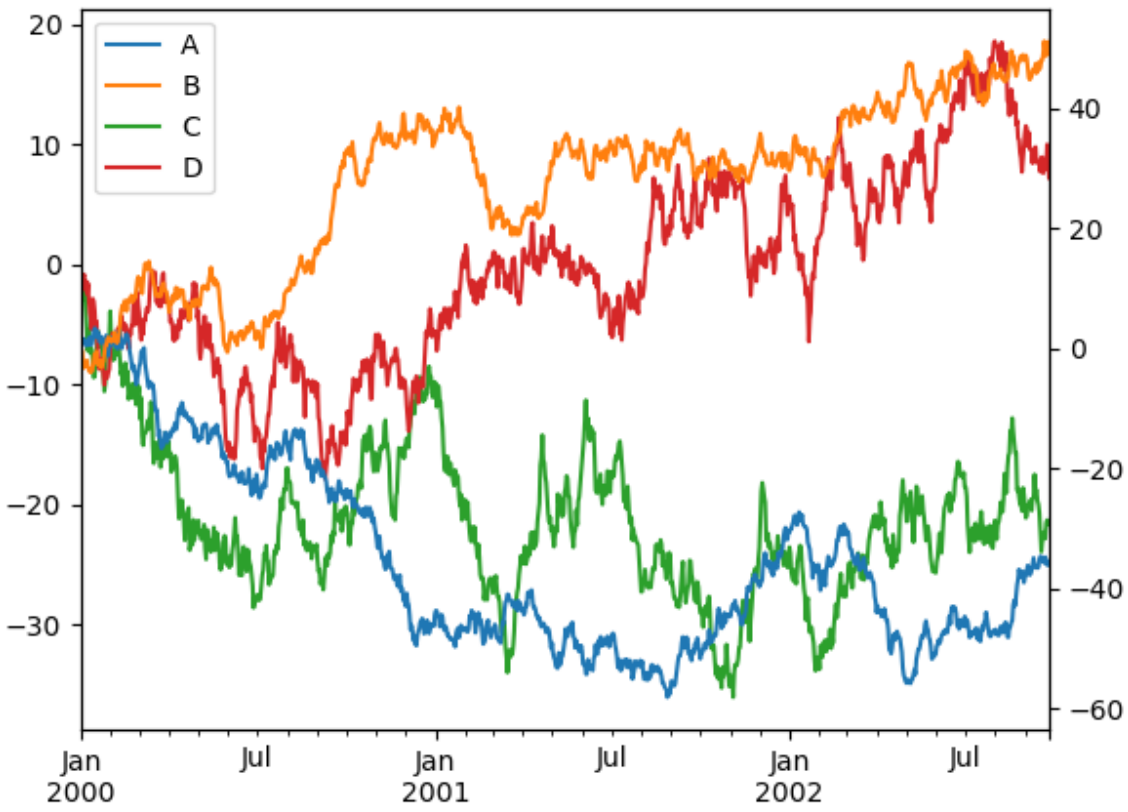
In [128]: ax.right_ax.set_ylabel("AB scale");
```



Note that the columns plotted on the secondary y-axis is automatically marked with "(right)" in the legend. To turn off the automatic marking, use the `mark_right=False` keyword:

```
In [129]: plt.figure();

In [130]: df.plot(secondary_y=["A", "B"], mark_right=False);
```



Custom formatters for timeseries plots

Changed in version 1.0.0.

pandas provides custom formatters for timeseries plots. These change the formatting of the axis labels for dates and times. By default, the custom formatters are applied only to plots created by pandas with `DataFrame.plot()` or `Series.plot()`. To have them apply to all plots, including those made by matplotlib, set the option `pd.options.plotting.matplotlib.register_converters = True` or use *pandas.plotting.register_matplotlib_converters()*.

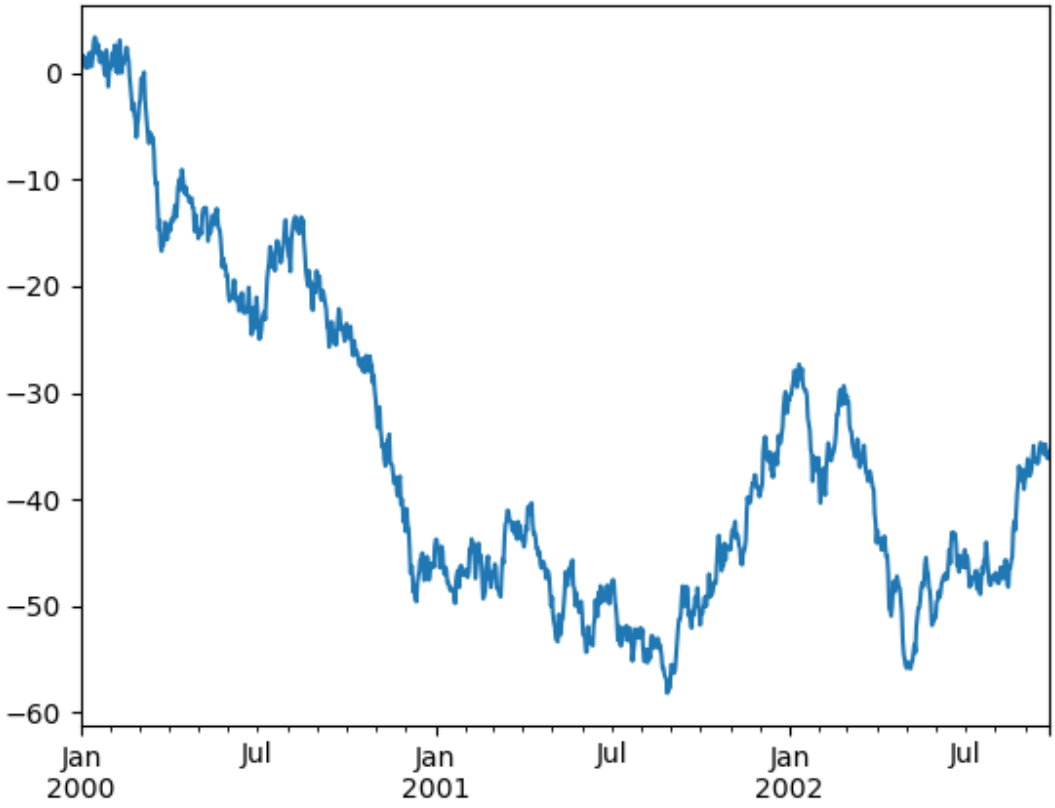
Suppressing tick resolution adjustment

pandas includes automatic tick resolution adjustment for regular frequency time-series data. For limited cases where pandas cannot infer the frequency information (e.g., in an externally created `twinx`), you can choose to suppress this behavior for alignment purposes.

Here is the default behavior, notice how the x-axis tick labeling is performed:

```
In [131]: plt.figure();

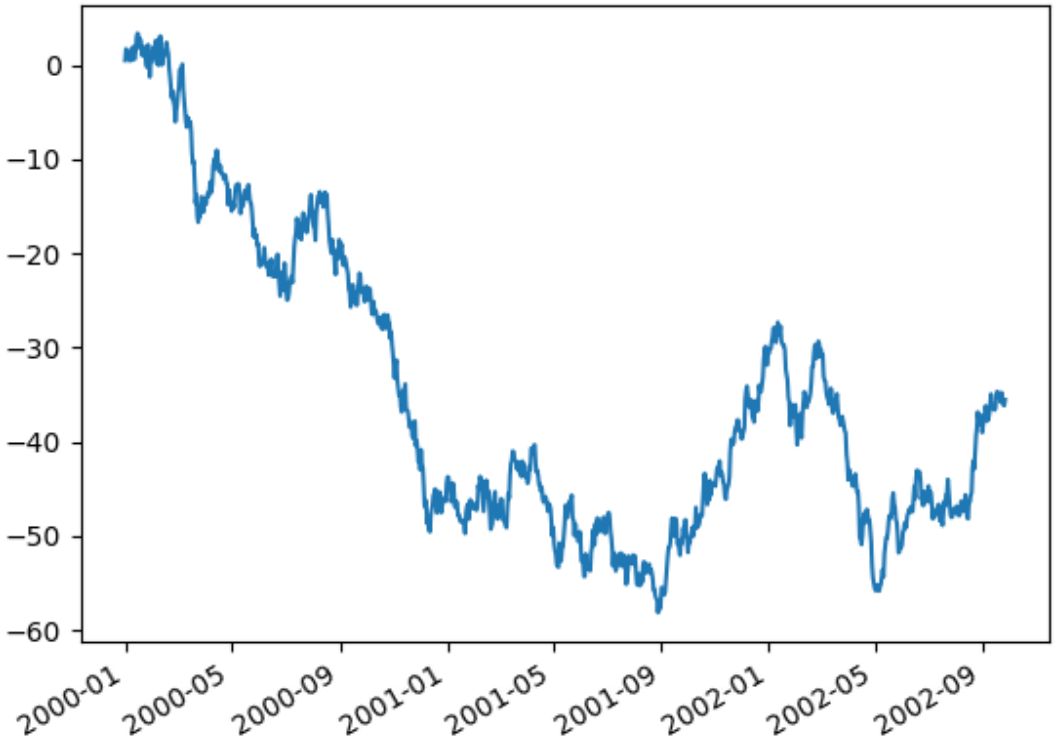
In [132]: df["A"].plot();
```



Using the `x_compat` parameter, you can suppress this behavior:

```
In [133]: plt.figure();

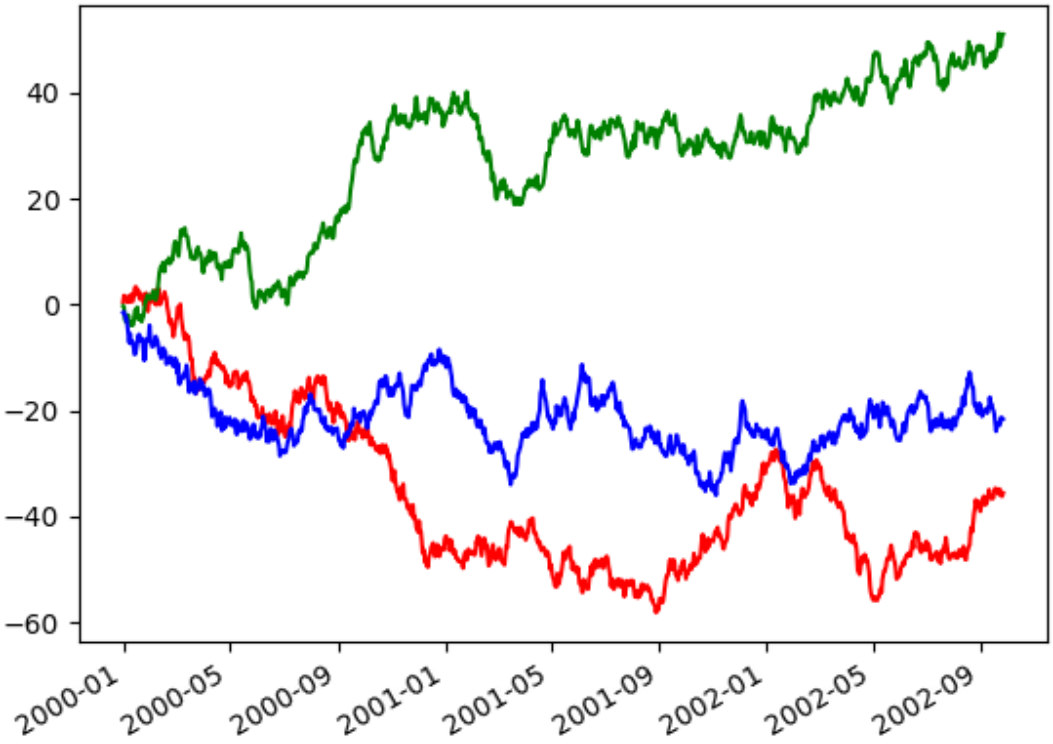
In [134]: df["A"].plot(x_compat=True);
```



If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plotting.plot_params` can be used in a `with` statement:

```
In [135]: plt.figure();

In [136]: with pd.plotting.plot_params.use("x_compat", True):
   .....:     df["A"].plot(color="r")
   .....:     df["B"].plot(color="g")
   .....:     df["C"].plot(color="b")
   .....:
```



Automatic date tick adjustment

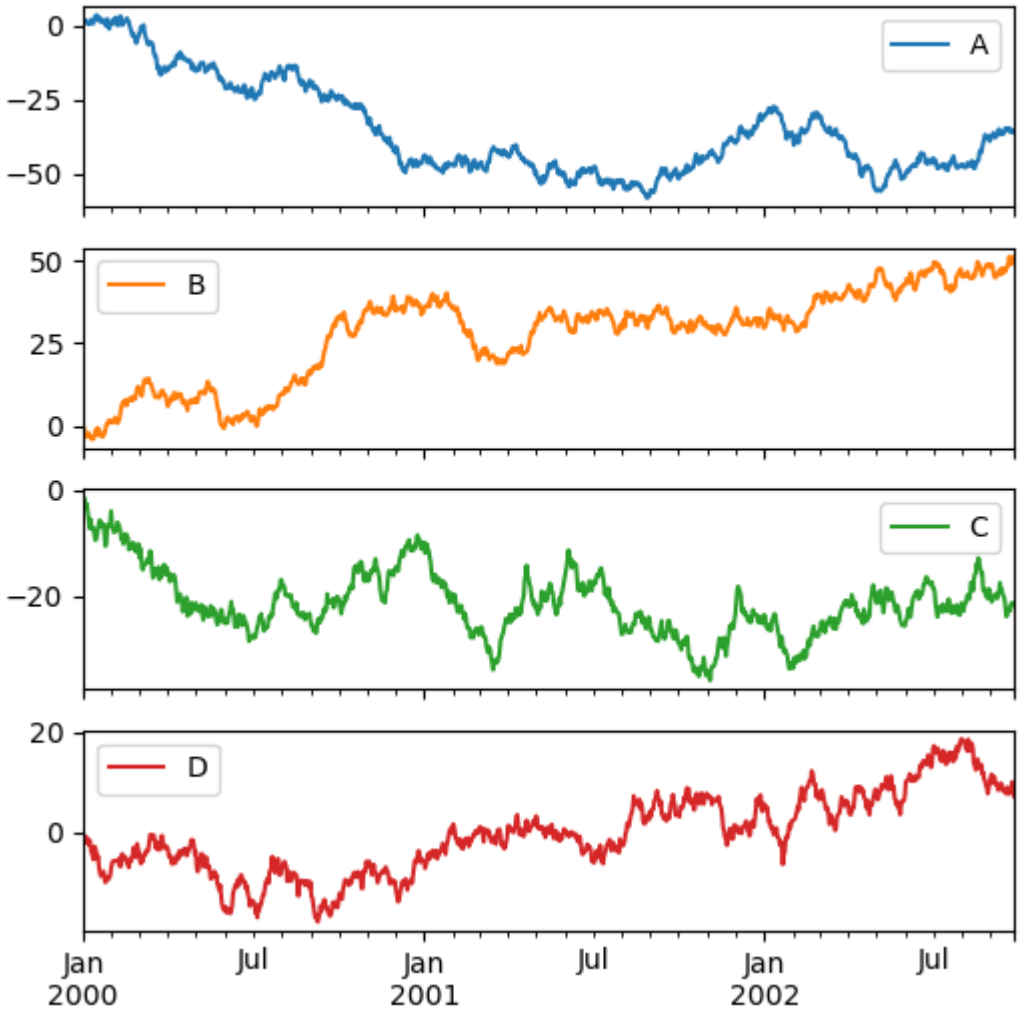
`TimedeltaIndex` now uses the native matplotlib tick locator methods, it is useful to call the automatic date tick adjustment from matplotlib for figures whose ticklabels overlap.

See the `autofmt_xdate` method and the matplotlib documentation for more.

Subplots

Each `Series` in a `DataFrame` can be plotted on a different axis with the `subplots` keyword:

```
In [137]: df.plot(subplots=True, figsize=(6, 6));
```

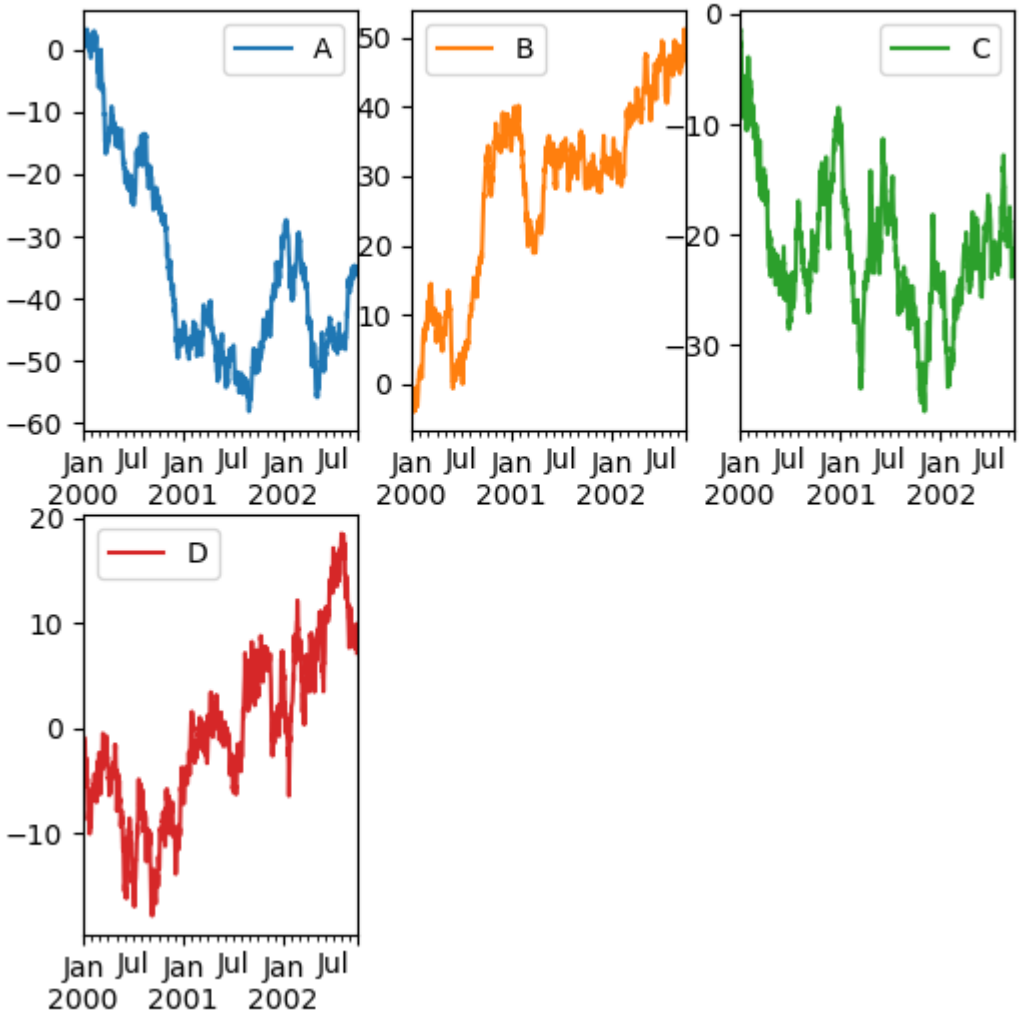


Using layout and targeting multiple axes

The layout of subplots can be specified by the `layout` keyword. It can accept `(rows, columns)`. The `layout` keyword can be used in `hist` and `boxplot` also. If the input is invalid, a `ValueError` will be raised.

The number of axes which can be contained by rows x columns specified by `layout` must be larger than the number of required subplots. If layout can contain more axes than required, blank axes are not drawn. Similar to a NumPy array's `reshape` method, you can use `-1` for one dimension to automatically calculate the number of rows or columns needed, given the other.

```
In [138]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);
```



The above example is identical to using:

```
In [139]: df.plot(subplots=True, layout=(2, -1), figsize=(6, 6), sharex=False);
```

The required number of columns (3) is inferred from the number of series to plot and the given number of rows (2).

You can pass multiple axes created beforehand as list-like via `ax` keyword. This allows more complicated layouts. The passed axes must be the same number as the subplots being drawn.

When multiple axes are passed via the `ax` keyword, `layout`, `sharex` and `sharey` keywords don't affect to the output. You should explicitly pass `sharex=False` and `sharey=False`, otherwise you will see a warning.

```
In [140]: fig, axes = plt.subplots(4, 4, figsize=(9, 9))

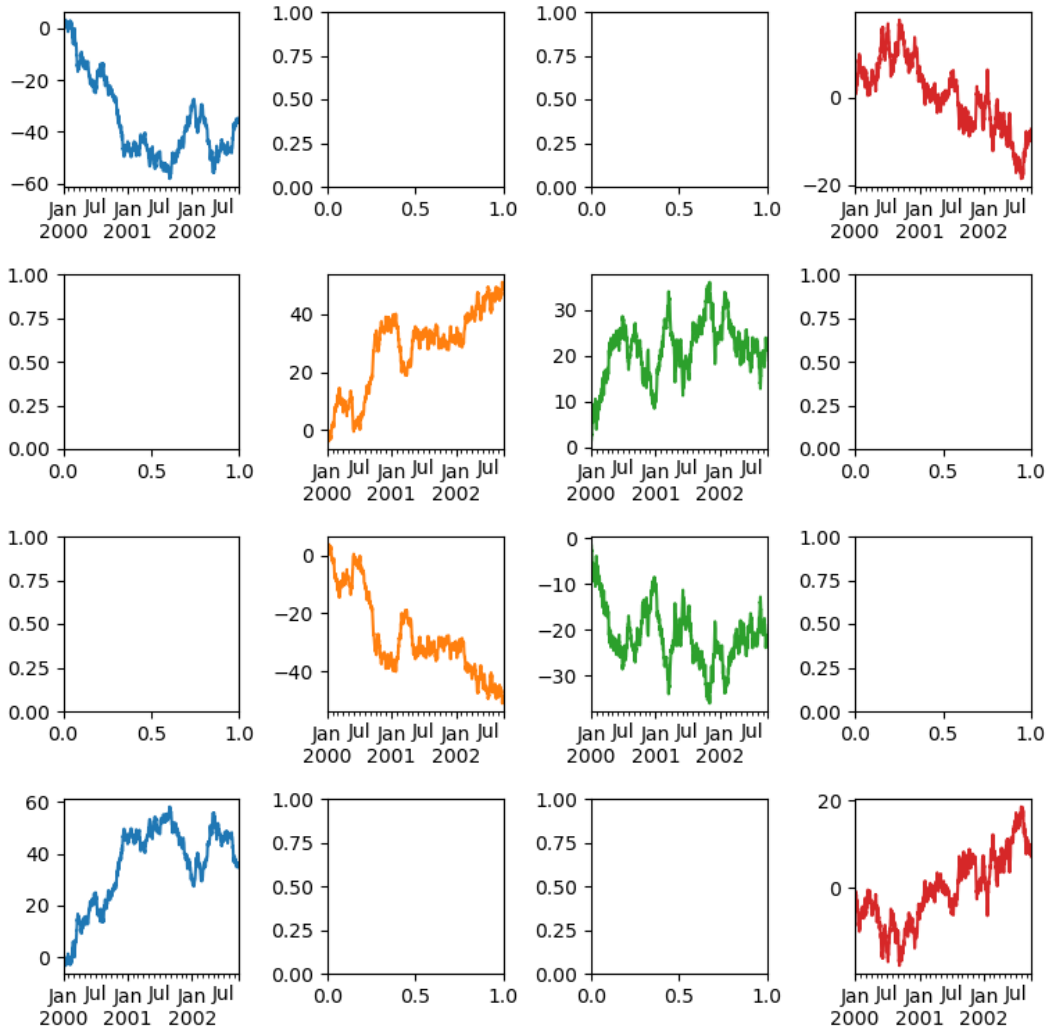
In [141]: plt.subplots_adjust(wspace=0.5, hspace=0.5)

In [142]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]

In [143]: target2 = [axes[3][0], axes[2][1], axes[1][2], axes[0][3]]

In [144]: df.plot(subplots=True, ax=target1, legend=False, sharex=False,␣
↪sharey=False);

In [145]: (-df).plot(subplots=True, ax=target2, legend=False, sharex=False,␣
↪sharey=False);
```



Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:

```
In [146]: fig, axes = plt.subplots(nrows=2, ncols=2)

In [147]: plt.subplots_adjust(wspace=0.2, hspace=0.5)

In [148]: df["A"].plot(ax=axes[0, 0]);

In [149]: axes[0, 0].set_title("A");

In [150]: df["B"].plot(ax=axes[0, 1]);

In [151]: axes[0, 1].set_title("B");

In [152]: df["C"].plot(ax=axes[1, 0]);
```

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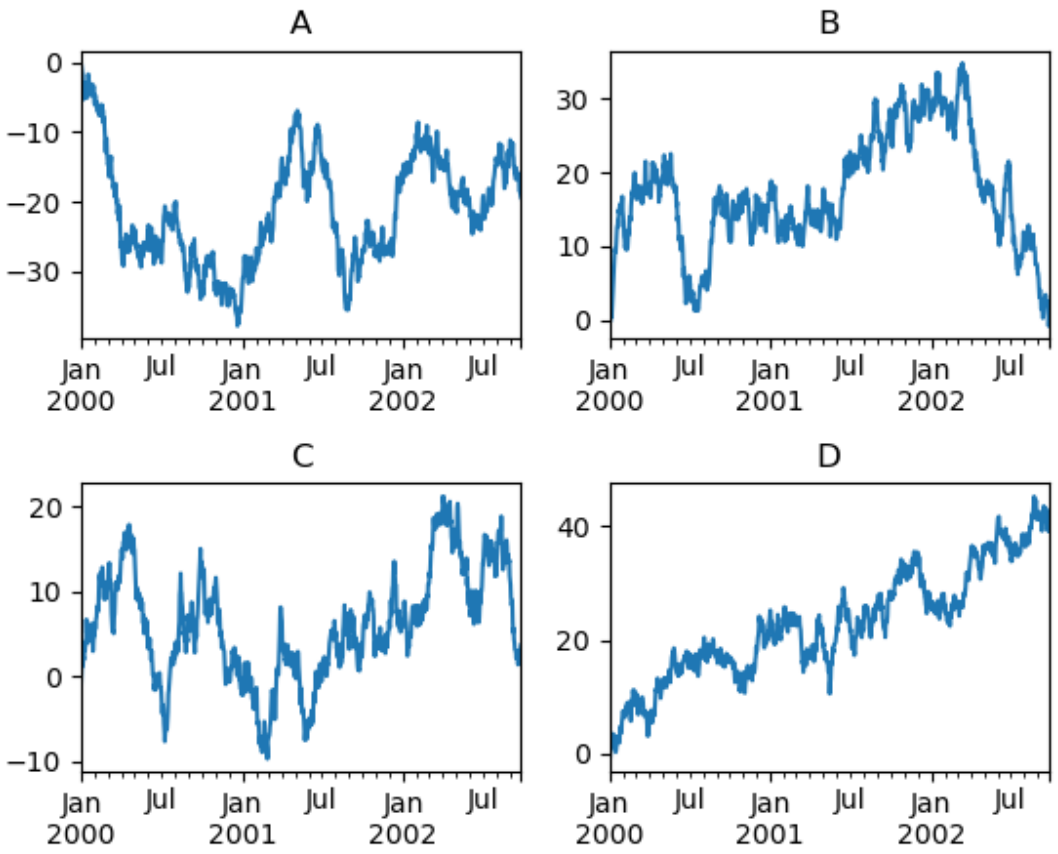
```
In [153]: axes[1, 0].set_title("C");

In [154]: df["D"].plot(ax=axes[1, 1]);

In [155]: axes[1, 1].set_title("D");
```



Plotting with error bars

Plotting with error bars is supported in `DataFrame.plot()` and `Series.plot()`.

Horizontal and vertical error bars can be supplied to the `xerr` and `yerr` keyword arguments to `plot()`. The error values can be specified using a variety of formats:

- As a `DataFrame` or `dict` of errors with column names matching the `columns` attribute of the plotting `DataFrame` or matching the `name` attribute of the `Series`.
- As a `str` indicating which of the columns of plotting `DataFrame` contain the error values.
- As raw values (`list`, `tuple`, or `np.ndarray`). Must be the same length as the plotting `DataFrame`/`Series`.

Asymmetrical error bars are also supported, however raw error values must be provided in this case. For a `N` length `Series`, a `2xN` array should be provided indicating lower and upper (or left and right) errors. For a `MxN` `DataFrame`, asymmetrical errors should be in a `Mx2xN` array.

Here is an example of one way to easily plot group means with standard deviations from the raw data.

```
# Generate the data
In [156]: ix3 = pd.MultiIndex.from_arrays(
   .....:     [
   .....:         ["a", "a", "a", "a", "b", "b", "b", "b"],
   .....:         ["foo", "foo", "bar", "bar", "foo", "foo", "bar", "bar"],
   .....:     ],
   .....:     names=["letter", "word"],
   .....: )
   .....:

In [157]: df3 = pd.DataFrame(
   .....:     {
   .....:         "data1": [3, 2, 4, 3, 2, 4, 3, 2],
   .....:         "data2": [6, 5, 7, 5, 4, 5, 6, 5],
   .....:     },
   .....:     index=ix3,
   .....: )
   .....:

# Group by index labels and take the means and standard deviations
# for each group
In [158]: gp3 = df3.groupby(level=("letter", "word"))

In [159]: means = gp3.mean()

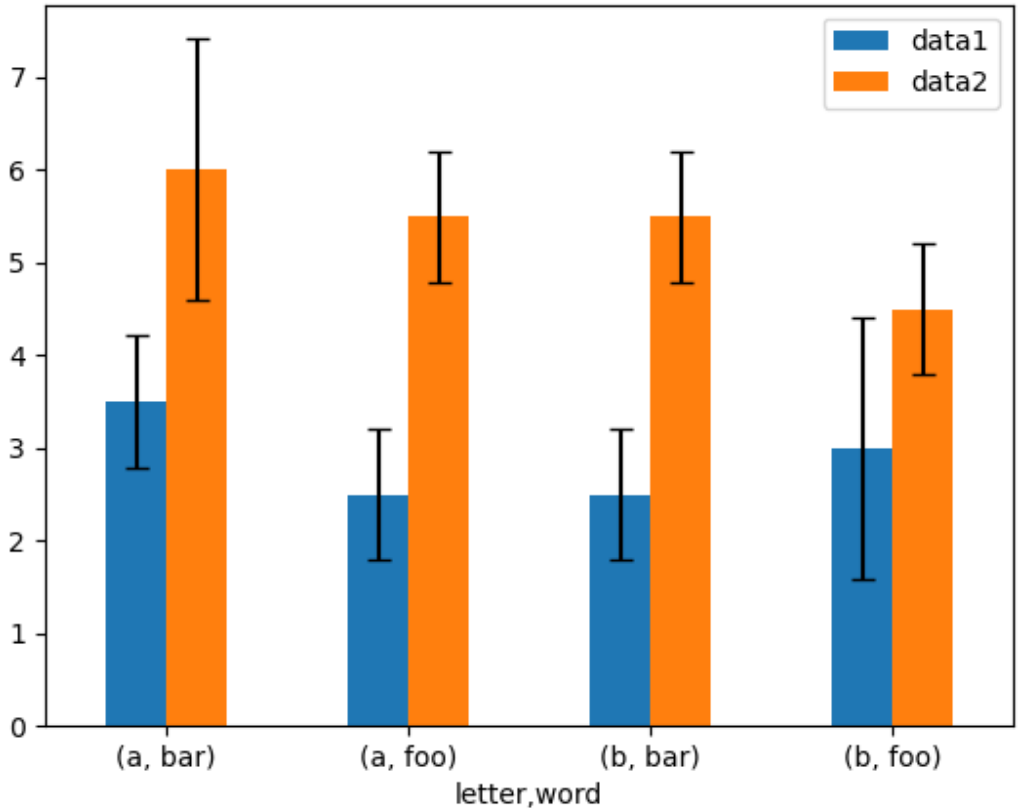
In [160]: errors = gp3.std()

In [161]: means
Out[161]:
             data1  data2
letter word
a      bar     3.5    6.0
       foo     2.5    5.5
b      bar     2.5    5.5
       foo     3.0    4.5

In [162]: errors
Out[162]:
                data1     data2
letter word
a      bar   0.707107  1.414214
       foo   0.707107  0.707107
b      bar   0.707107  0.707107
       foo   1.414214  0.707107

# Plot
In [163]: fig, ax = plt.subplots()

In [164]: means.plot.bar(yerr=errors, ax=ax, capsize=4, rot=0);
```



Plotting tables

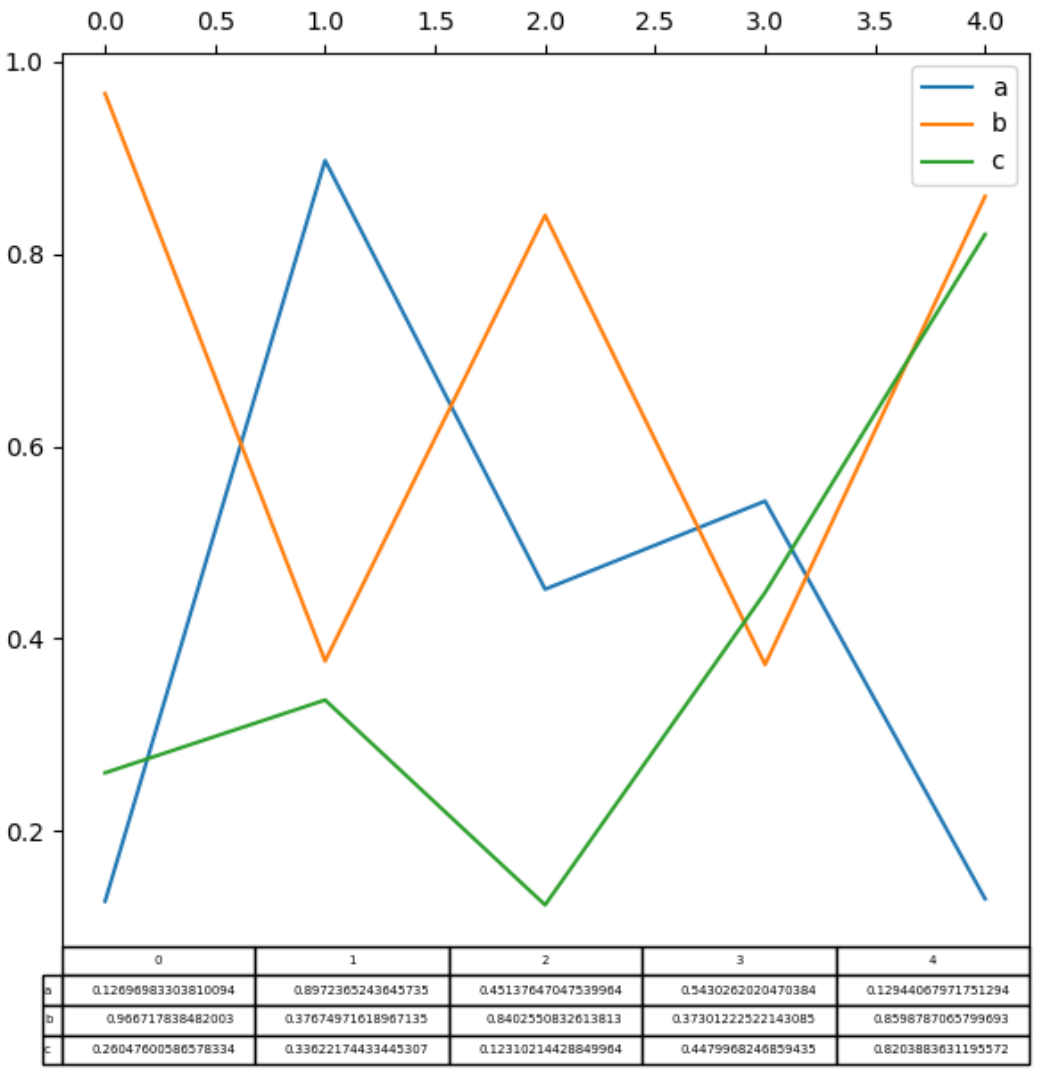
Plotting with matplotlib table is now supported in `DataFrame.plot()` and `Series.plot()` with a `table` keyword. The `table` keyword can accept `bool`, `DataFrame` or `Series`. The simple way to draw a table is to specify `table=True`. Data will be transposed to meet matplotlib's default layout.

```
In [165]: fig, ax = plt.subplots(1, 1, figsize=(7, 6.5))

In [166]: df = pd.DataFrame(np.random.rand(5, 3), columns=["a", "b", "c"])

In [167]: ax.xaxis.tick_top()  # Display x-axis ticks on top.

In [168]: df.plot(table=True, ax=ax);
```



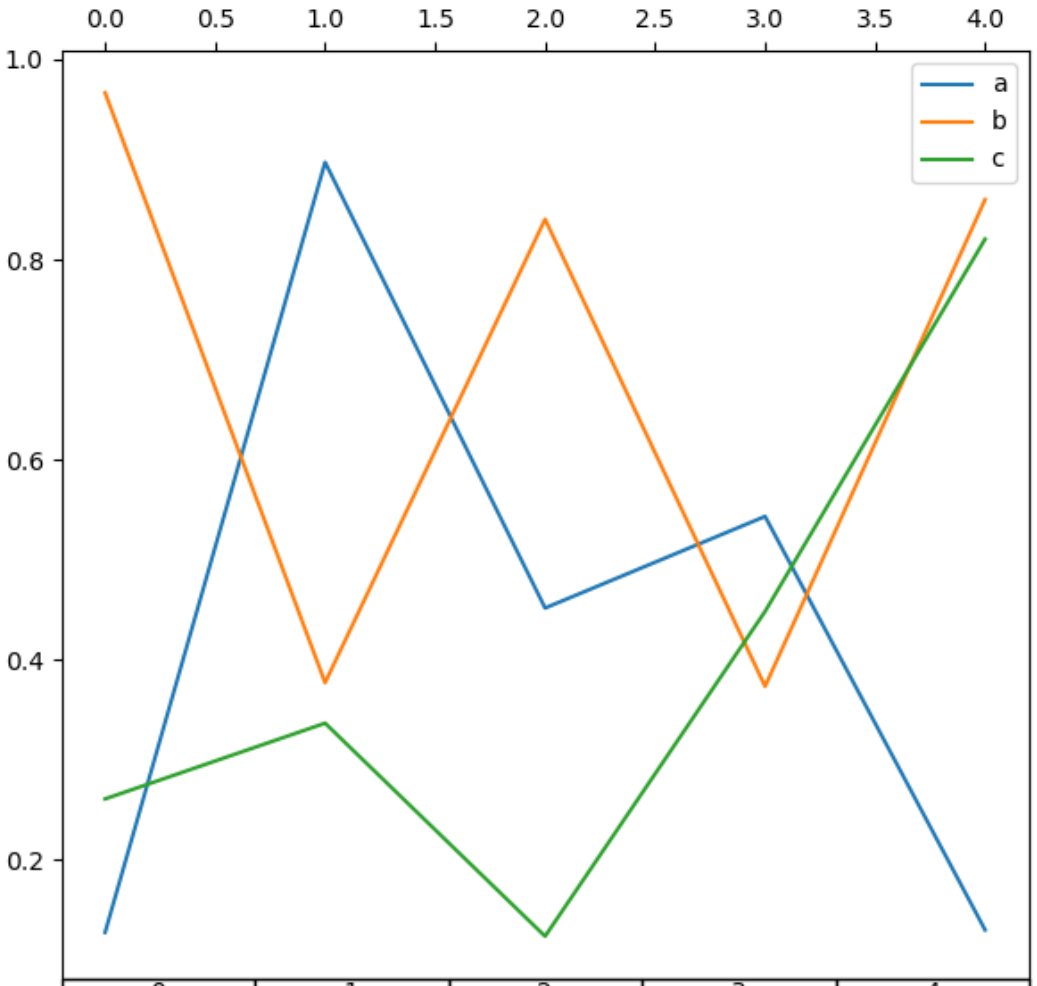
	0	1	2	3	4
a	0.12696983303810094	0.8972365243645735	0.45137647047539964	0.5430262020470384	0.12944067971751294
b	0.966717838482003	0.37674971618967135	0.8402550832613813	0.37301222522143085	0.8598787065799693
c	0.26047600586578334	0.33622174433445307	0.12310214428849964	0.4479968246859435	0.8203883631195572

Also, you can pass a different `DataFrame` or `Series` to the `table` keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as seen in the example below.

```
In [169]: fig, ax = plt.subplots(1, 1, figsize=(7, 6.75))

In [170]: ax.xaxis.tick_top()  # Display x-axis ticks on top.

In [171]: df.plot(table=np.round(df.T, 2), ax=ax);
```



	0	1	2	3	4
a	0.13	0.9	0.45	0.54	0.13
b	0.97	0.38	0.84	0.37	0.86
c	0.26	0.34	0.12	0.45	0.82

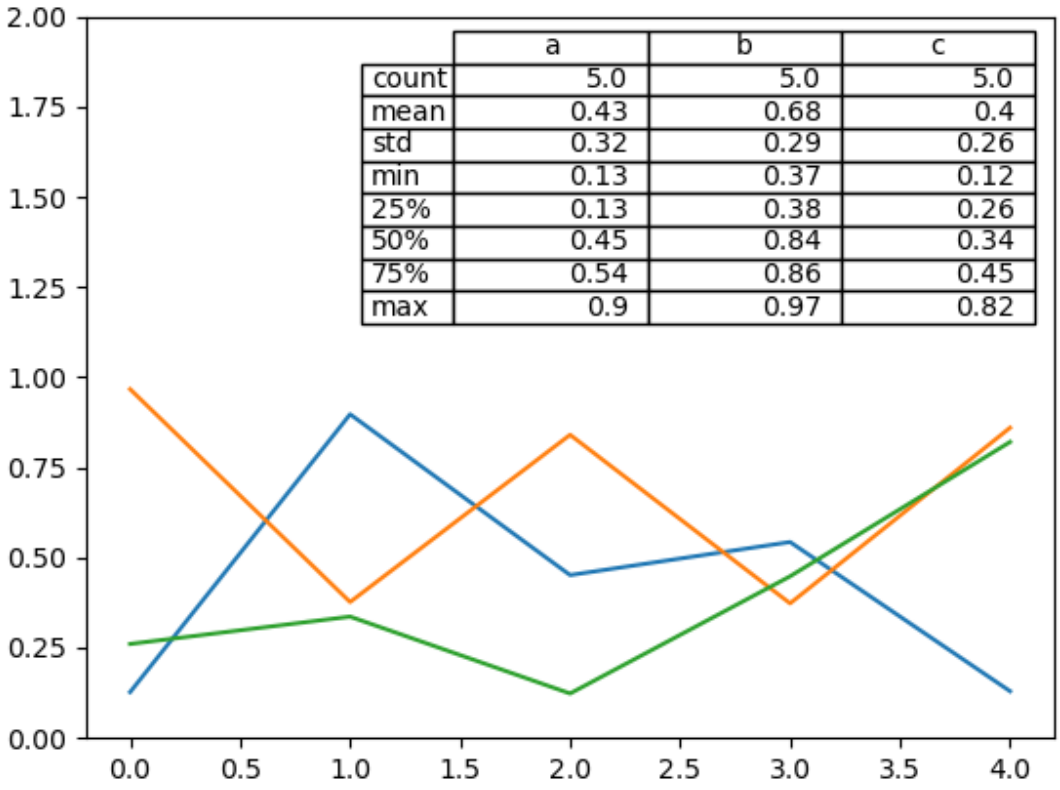
There also exists a helper function `pandas.plotting.table`, which creates a table from `DataFrame` or `Series`, and adds it to an `matplotlib.Axes` instance. This function can accept keywords which the matplotlib table has.

```
In [172]: from pandas.plotting import table

In [173]: fig, ax = plt.subplots(1, 1)

In [174]: table(ax, np.round(df.describe(), 2), loc="upper right", colWidths=[0.2, 0.
↪2, 0.2]);

In [175]: df.plot(ax=ax, ylim=(0, 2), legend=None);
```



	a	b	c
count	5.0	5.0	5.0
mean	0.43	0.68	0.4
std	0.32	0.29	0.26
min	0.13	0.37	0.12
25%	0.13	0.38	0.26
50%	0.45	0.84	0.34
75%	0.54	0.86	0.45
max	0.9	0.97	0.82

Note: You can get table instances on the axes using `axes.tables` property for further decorations. See the matplotlib table documentation for more.

Colormaps

A potential issue when plotting a large number of columns is that it can be difficult to distinguish some series due to repetition in the default colors. To remedy this, `DataFrame` plotting supports the use of the `colormap` argument, which accepts either a Matplotlib colormap or a string that is a name of a colormap registered with Matplotlib. A visualization of the default matplotlib colormaps is available here.

As matplotlib does not directly support colormaps for line-based plots, the colors are selected based on an even spacing determined by the number of columns in the `DataFrame`. There is no consideration made for background color, so some colormaps will produce lines that are not easily visible.

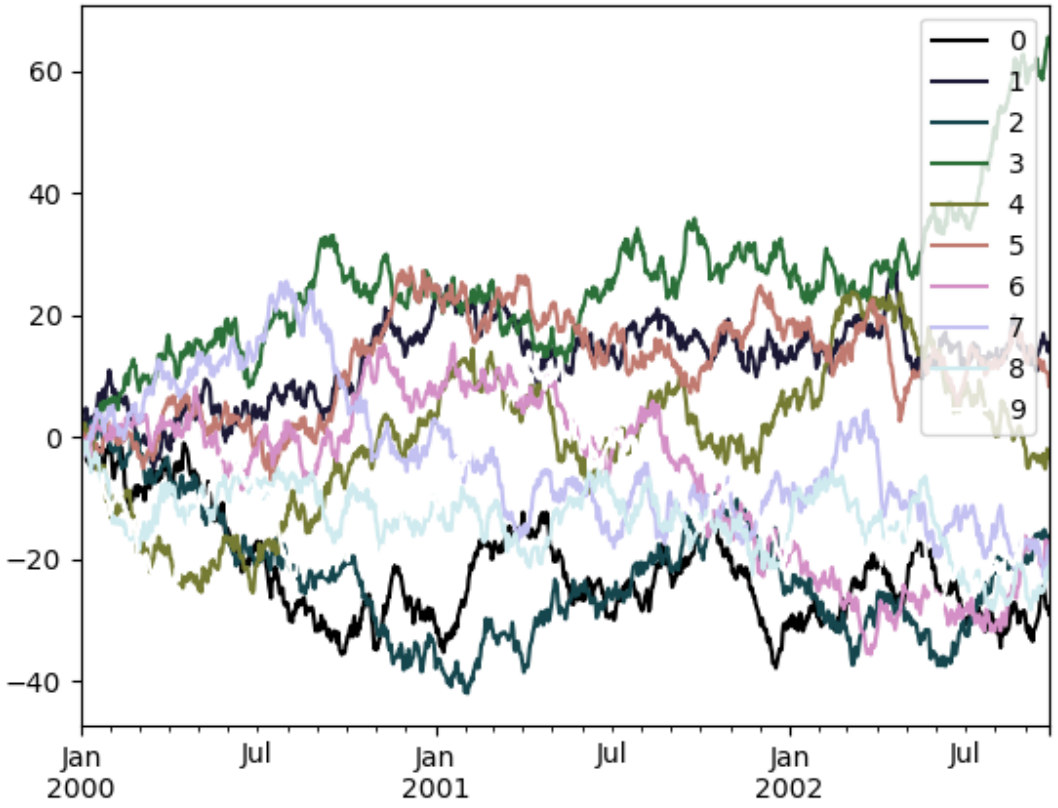
To use the cubehelix colormap, we can pass `colormap='cubehelix'`.

```
In [176]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)

In [177]: df = df.cumsum()

In [178]: plt.figure();

In [179]: df.plot(colormap="cubehelix");
```

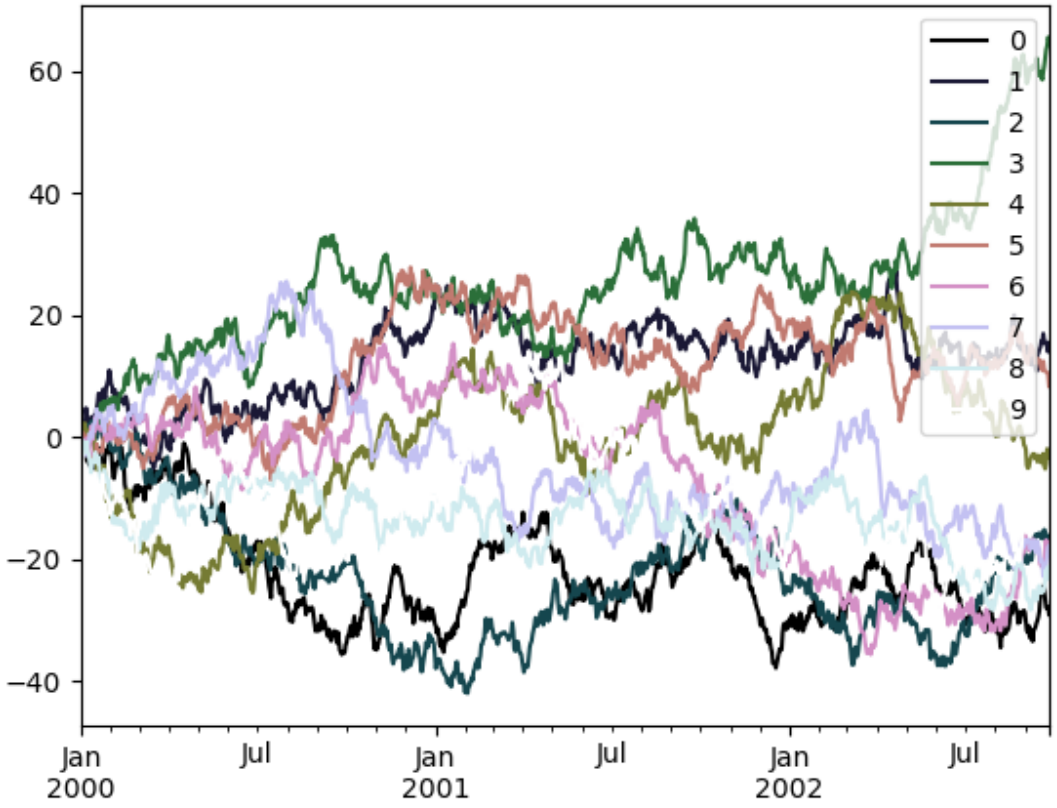


Alternatively, we can pass the colormap itself:

```
In [180]: from matplotlib import cm

In [181]: plt.figure();

In [182]: df.plot(colormap=cm.cubehelix);
```



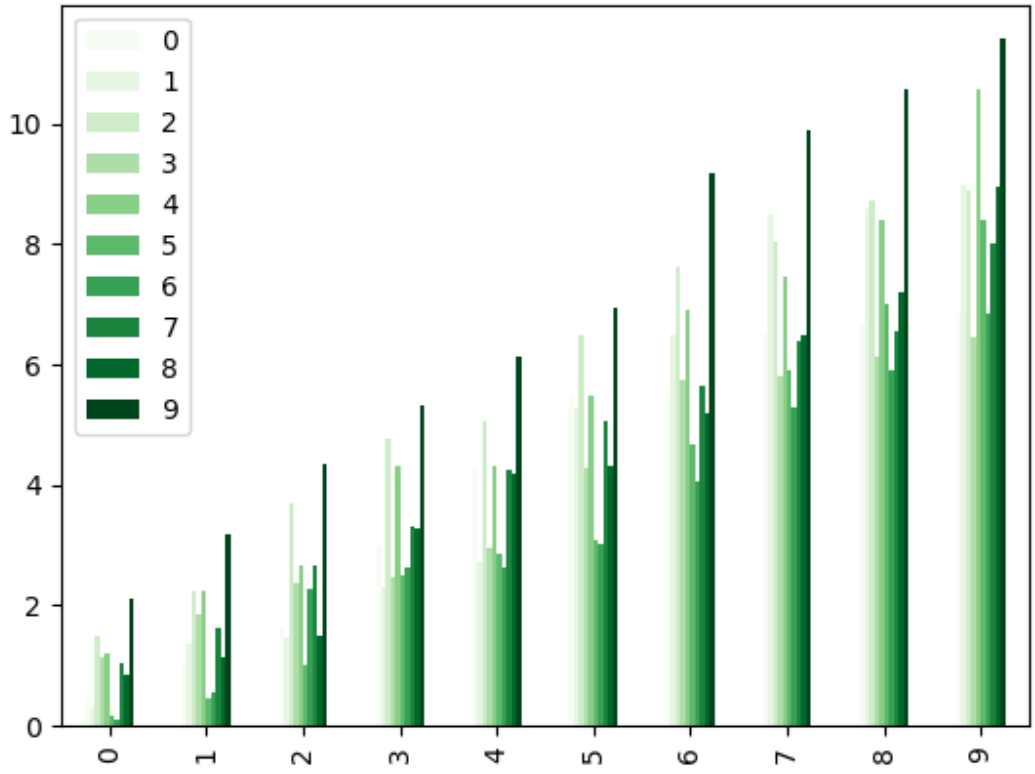
Colormaps can also be used other plot types, like bar charts:

```
In [183]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)

In [184]: dd = dd.cumsum()

In [185]: plt.figure();

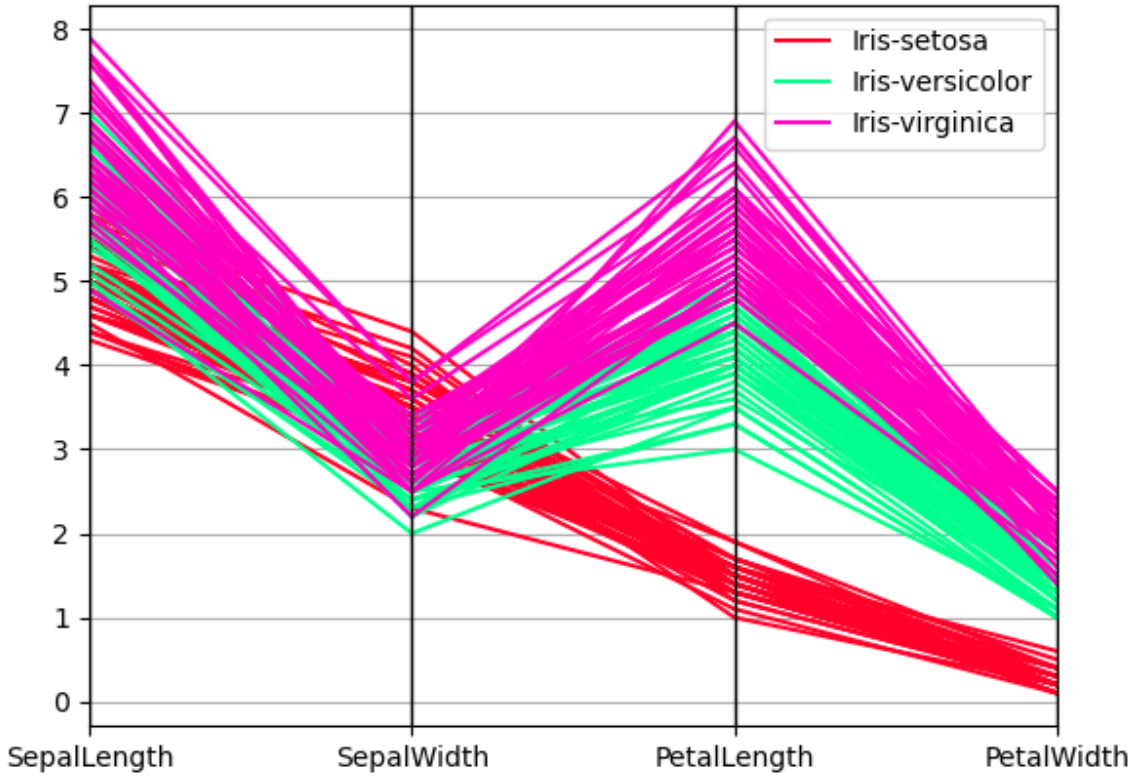
In [186]: dd.plot.bar(colormap="Greens");
```



Parallel coordinates charts:

```
In [187]: plt.figure();

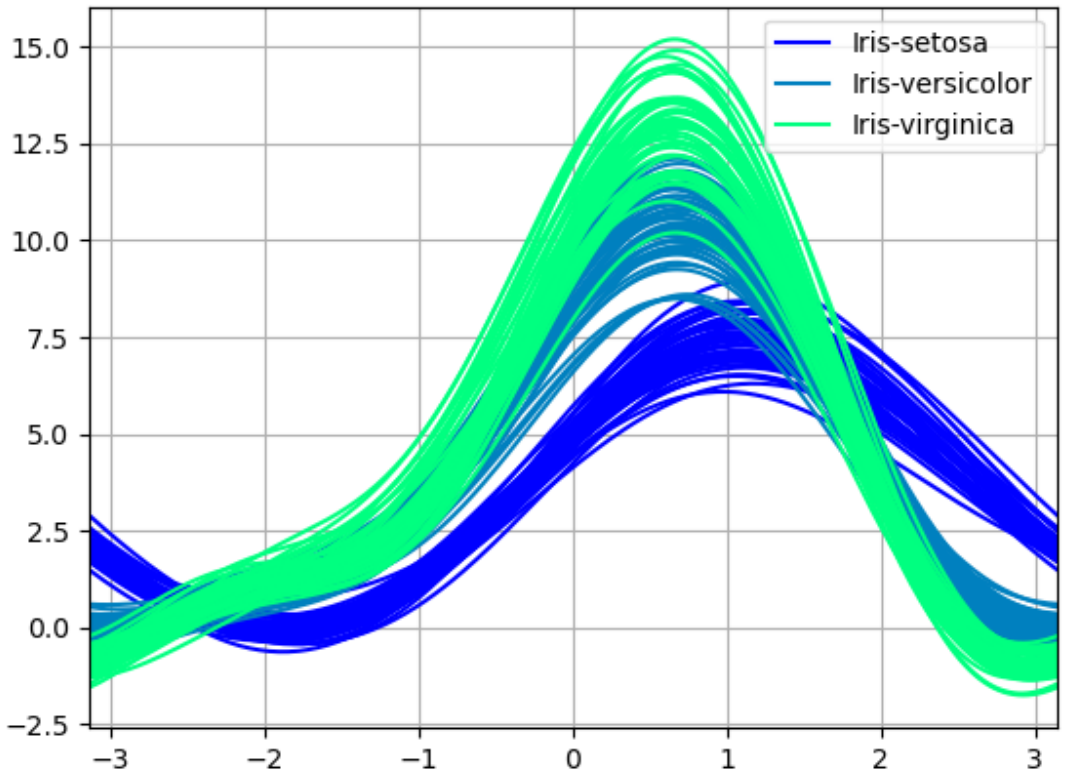
In [188]: parallel_coordinates(data, "Name", colormap="gist_rainbow");
```



Andrews curves charts:

```
In [189]: plt.figure();

In [190]: andrews_curves(data, "Name", colormap="winter");
```



2.15.6 Plotting directly with matplotlib

In some situations it may still be preferable or necessary to prepare plots directly with matplotlib, for instance when a certain type of plot or customization is not (yet) supported by pandas. `Series` and `DataFrame` objects behave like arrays and can therefore be passed directly to matplotlib functions without explicit casts.

pandas also automatically registers formatters and locators that recognize date indices, thereby extending date and time support to practically all plot types available in matplotlib. Although this formatting does not provide the same level of refinement you would get when plotting via pandas, it can be faster when plotting a large number of points.

```
In [191]: price = pd.Series(
   .....:     np.random.randn(150).cumsum(),
   .....:     index=pd.date_range("2000-1-1", periods=150, freq="B"),
   .....: )
   .....:

In [192]: ma = price.rolling(20).mean()

In [193]: mstd = price.rolling(20).std()

In [194]: plt.figure();

In [195]: plt.plot(price.index, price, "k");
```

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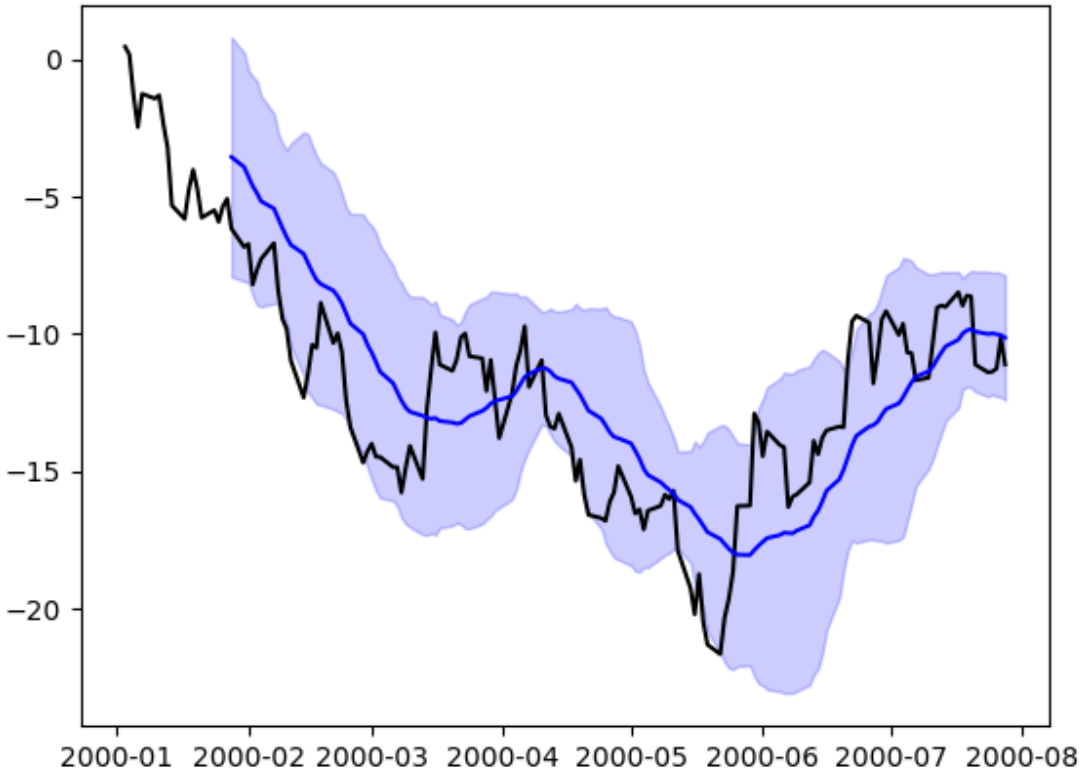
```
In [196]: plt.plot(ma.index, ma, "b");

In [197]: plt.fill_between(mstd.index, ma - 2 * mstd, ma + 2 * mstd, color="b",␣
↪alpha=0.2);
```



2.15.7 Plotting backends

Starting in version 0.25, pandas can be extended with third-party plotting backends. The main idea is letting users select a plotting backend different than the provided one based on Matplotlib.

This can be done by passsing 'backend.module' as the argument `backend` in `plot` function. For example:

```
>>> Series([1, 2, 3]).plot(backend="backend.module")
```

Alternatively, you can also set this option globally, do you don't need to specify the keyword in each `plot` call. For example:

```
>>> pd.set_option("plotting.backend", "backend.module")
>>> pd.Series([1, 2, 3]).plot()
```

Or:

```
>>> pd.options.plotting.backend = "backend.module"
>>> pd.Series([1, 2, 3]).plot()
```

This would be more or less equivalent to:

```
>>> import backend.module
>>> backend.module.plot(pd.Series([1, 2, 3]))
```

The backend module can then use other visualization tools (Bokeh, Altair, hvplot,...) to generate the plots. Some libraries implementing a backend for pandas are listed on the ecosystem ecosystem.visualization page.

Developers guide can be found at https://pandas.pydata.org/docs/dev/development/extending.html#plotting-backends

2.16 Computational tools

2.16.1 Statistical functions

Percent change

`Series` and `DataFrame` have a method *`pct_change()`* to compute the percent change over a given number of periods (using `fill_method` to fill NA/null values *before* computing the percent change).

```
In [1]: ser = pd.Series(np.random.randn(8))

In [2]: ser.pct_change()
Out[2]:
0         NaN
1   -1.602976
2    4.334938
3   -0.247456
4   -2.067345
5   -1.142903
6   -1.688214
7   -9.759729
dtype: float64
```

```
In [3]: df = pd.DataFrame(np.random.randn(10, 4))

In [4]: df.pct_change(periods=3)
Out[4]:
          0         1         2         3
0       NaN       NaN       NaN       NaN
1       NaN       NaN       NaN       NaN
2       NaN       NaN       NaN       NaN
3 -0.218320 -1.054001  1.987147 -0.510183
4 -0.439121 -1.816454  0.649715 -4.822809
5 -0.127833 -3.042065 -5.866604 -1.776977
6 -2.596833 -1.959538 -2.111697 -3.798900
7 -0.117826 -2.169058  0.036094 -0.067696
8  2.492606 -1.357320 -1.205802 -1.558697
9 -1.012977  2.324558 -1.003744 -0.371806
```

Covariance

Series.cov() can be used to compute covariance between series (excluding missing values).

```
In [5]: s1 = pd.Series(np.random.randn(1000))

In [6]: s2 = pd.Series(np.random.randn(1000))

In [7]: s1.cov(s2)
Out[7]: 0.0006801088174310875
```

Analogously, *DataFrame.cov()* to compute pairwise covariances among the series in the DataFrame, also excluding NA/null values.

Note: Assuming the missing data are missing at random this results in an estimate for the covariance matrix which is unbiased. However, for many applications this estimate may not be acceptable because the estimated covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimated correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

```
In [8]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=["a", "b", "c", "d", "e
↪"])

In [9]: frame.cov()
Out[9]:
          a         b         c         d         e
a  1.000882 -0.003177 -0.002698 -0.006889  0.031912
b -0.003177  1.024721  0.000191  0.009212  0.000857
c -0.002698  0.000191  0.950735 -0.031743 -0.005087
d -0.006889  0.009212 -0.031743  1.002983 -0.047952
e  0.031912  0.000857 -0.005087 -0.047952  1.042487
```

`DataFrame.cov` also supports an optional `min_periods` keyword that specifies the required minimum number of observations for each column pair in order to have a valid result.

```
In [10]: frame = pd.DataFrame(np.random.randn(20, 3), columns=["a", "b", "c"])

In [11]: frame.loc[frame.index[:5], "a"] = np.nan

In [12]: frame.loc[frame.index[5:10], "b"] = np.nan

In [13]: frame.cov()
Out[13]:
          a         b         c
a  1.123670 -0.412851  0.018169
b -0.412851  1.154141  0.305260
c  0.018169  0.305260  1.301149

In [14]: frame.cov(min_periods=12)
Out[14]:
          a         b         c
a  1.123670       NaN  0.018169
b       NaN  1.154141  0.305260
c  0.018169  0.305260  1.301149
```

Correlation

Correlation may be computed using the *corr()* method. Using the `method` parameter, several methods for computing correlations are provided:

Method name	Description
`pearson (default)`	Standard correlation coefficient
`kendall`	Kendall Tau correlation coefficient
`spearman`	Spearman rank correlation coefficient

All of these are currently computed using pairwise complete observations. Wikipedia has articles covering the above correlation coefficients:

- Pearson correlation coefficient
- Kendall rank correlation coefficient
- Spearman's rank correlation coefficient

Note: Please see the *caveats* associated with this method of calculating correlation matrices in the *covariance section*.

```
In [15]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=["a", "b", "c", "d",
↪"e"])

In [16]: frame.iloc[::2] = np.nan

# Series with Series
In [17]: frame["a"].corr(frame["b"])
Out[17]: 0.013479040400098775

In [18]: frame["a"].corr(frame["b"], method="spearman")
Out[18]: -0.007289885159540637

# Pairwise correlation of DataFrame columns
In [19]: frame.corr()
Out[19]:
          a         b         c         d         e
a  1.000000  0.013479 -0.049269 -0.042239 -0.028525
b  0.013479  1.000000 -0.020433 -0.011139  0.005654
c -0.049269 -0.020433  1.000000  0.018587 -0.054269
d -0.042239 -0.011139  0.018587  1.000000 -0.017060
e -0.028525  0.005654 -0.054269 -0.017060  1.000000
```

Note that non-numeric columns will be automatically excluded from the correlation calculation.

Like `cov`, `corr` also supports the optional `min_periods` keyword:

```
In [20]: frame = pd.DataFrame(np.random.randn(20, 3), columns=["a", "b", "c"])

In [21]: frame.loc[frame.index[:5], "a"] = np.nan

In [22]: frame.loc[frame.index[5:10], "b"] = np.nan

In [23]: frame.corr()
Out[23]:
```

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```
          a         b         c
a  1.000000 -0.121111  0.069544
b -0.121111  1.000000  0.051742
c  0.069544  0.051742  1.000000

In [24]: frame.corr(min_periods=12)
Out[24]:
          a         b         c
a  1.000000       NaN  0.069544
b       NaN  1.000000  0.051742
c  0.069544  0.051742  1.000000
```

New in version 0.24.0.

The `method` argument can also be a callable for a generic correlation calculation. In this case, it should be a single function that produces a single value from two ndarray inputs. Suppose we wanted to compute the correlation based on histogram intersection:

```
# histogram intersection
In [25]: def histogram_intersection(a, b):
   ....:     return np.minimum(np.true_divide(a, a.sum()), np.true_divide(b, b.
↪sum())).sum()
   ....:

In [26]: frame.corr(method=histogram_intersection)
Out[26]:
          a          b          c
a  1.000000  -6.404882  -2.058431
b -6.404882   1.000000 -19.255743
c -2.058431 -19.255743   1.000000
```

A related method *corrwith()* is implemented on DataFrame to compute the correlation between like-labeled Series contained in different DataFrame objects.

```
In [27]: index = ["a", "b", "c", "d", "e"]

In [28]: columns = ["one", "two", "three", "four"]

In [29]: df1 = pd.DataFrame(np.random.randn(5, 4), index=index, columns=columns)

In [30]: df2 = pd.DataFrame(np.random.randn(4, 4), index=index[:4], columns=columns)

In [31]: df1.corrwith(df2)
Out[31]:
one     -0.125501
two     -0.493244
three    0.344056
four     0.004183
dtype: float64

In [32]: df2.corrwith(df1, axis=1)
Out[32]:
a   -0.675817
b    0.458296
c    0.190809
d   -0.186275
e         NaN
```

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```
dtype: float64
```

Data ranking

The *rank()* method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

```
In [33]: s = pd.Series(np.random.randn(5), index=list("abcde"))

In [34]: s["d"] = s["b"]  # so there's a tie

In [35]: s.rank()
Out[35]:
a    5.0
b    2.5
c    1.0
d    2.5
e    4.0
dtype: float64
```

rank() is also a DataFrame method and can rank either the rows (`axis=0`) or the columns (`axis=1`). `NaN` values are excluded from the ranking.

```
In [36]: df = pd.DataFrame(np.random.randn(10, 6))

In [37]: df[4] = df[2][:5]  # some ties

In [38]: df
Out[38]:
          0         1         2         3         4         5
0 -0.904948 -1.163537 -1.457187  0.135463 -1.457187  0.294650
1 -0.976288 -0.244652 -0.748406 -0.999601 -0.748406 -0.800809
2  0.401965  1.460840  1.256057  1.308127  1.256057  0.876004
3  0.205954  0.369552 -0.669304  0.038378 -0.669304  1.140296
4 -0.477586 -0.730705 -1.129149 -0.601463 -1.129149 -0.211196
5 -1.092970 -0.689246  0.908114  0.204848       NaN  0.463347
6  0.376892  0.959292  0.095572 -0.593740       NaN -0.069180
7 -1.002601  1.957794 -0.120708  0.094214       NaN -1.467422
8 -0.547231  0.664402 -0.519424 -0.073254       NaN -1.263544
9 -0.250277 -0.237428 -1.056443  0.419477       NaN  1.375064

In [39]: df.rank(1)
Out[39]:
     0    1    2    3    4    5
0  4.0  3.0  1.5  5.0  1.5  6.0
1  2.0  6.0  4.5  1.0  4.5  3.0
2  1.0  6.0  3.5  5.0  3.5  2.0
3  4.0  5.0  1.5  3.0  1.5  6.0
4  5.0  3.0  1.5  4.0  1.5  6.0
5  1.0  2.0  5.0  3.0  NaN  4.0
6  4.0  5.0  3.0  1.0  NaN  2.0
7  2.0  5.0  3.0  4.0  NaN  1.0
8  2.0  5.0  3.0  4.0  NaN  1.0
9  2.0  3.0  1.0  4.0  NaN  5.0
```

`rank` optionally takes a parameter `ascending` which by default is true; when false, data is reverse-ranked, with larger values assigned a smaller rank.

`rank` supports different tie-breaking methods, specified with the `method` parameter:

- `average` : average rank of tied group
- `min` : lowest rank in the group
- `max` : highest rank in the group
- `first` : ranks assigned in the order they appear in the array

Windowing functions

See *the window operations user guide* for an overview of windowing functions.

2.17 Group by: split-apply-combine

By "group by" we are referring to a process involving one or more of the following steps:

- **Splitting** the data into groups based on some criteria.
- **Applying** a function to each group independently.
- **Combining** the results into a data structure.

Out of these, the split step is the most straightforward. In fact, in many situations we may wish to split the data set into groups and do something with those groups. In the apply step, we might wish to do one of the following:

- **Aggregation**: compute a summary statistic (or statistics) for each group. Some examples:
  - Compute group sums or means.
  - Compute group sizes / counts.
- **Transformation**: perform some group-specific computations and return a like-indexed object. Some examples:
  - Standardize data (zscore) within a group.
  - Filling NAs within groups with a value derived from each group.
- **Filtration**: discard some groups, according to a group-wise computation that evaluates True or False. Some examples:
  - Discard data that belongs to groups with only a few members.
  - Filter out data based on the group sum or mean.
- Some combination of the above: GroupBy will examine the results of the apply step and try to return a sensibly combined result if it doesn't fit into either of the above two categories.

Since the set of object instance methods on pandas data structures are generally rich and expressive, we often simply want to invoke, say, a DataFrame function on each group. The name GroupBy should be quite familiar to those who have used a SQL-based tool (or `itertools`), in which you can write code like:

```
SELECT Column1, Column2, mean(Column3), sum(Column4)
FROM SomeTable
GROUP BY Column1, Column2
```

We aim to make operations like this natural and easy to express using pandas. We'll address each area of GroupBy functionality then provide some non-trivial examples / use cases.

See the *cookbook* for some advanced strategies.

2.17.1 Splitting an object into groups

pandas objects can be split on any of their axes. The abstract definition of grouping is to provide a mapping of labels to group names. To create a GroupBy object (more on what the GroupBy object is later), you may do the following:

```
In [1]: df = pd.DataFrame(
   ...:     [
   ...:         ("bird", "Falconiformes", 389.0),
   ...:         ("bird", "Psittaciformes", 24.0),
   ...:         ("mammal", "Carnivora", 80.2),
   ...:         ("mammal", "Primates", np.nan),
   ...:         ("mammal", "Carnivora", 58),
   ...:     ],
   ...:     index=["falcon", "parrot", "lion", "monkey", "leopard"],
   ...:     columns=("class", "order", "max_speed"),
   ...: )
   ...:

In [2]: df
Out[2]:
          class           order  max_speed
falcon     bird   Falconiformes      389.0
parrot     bird  Psittaciformes       24.0
lion     mammal       Carnivora       80.2
monkey   mammal        Primates        NaN
leopard  mammal       Carnivora       58.0

# default is axis=0
In [3]: grouped = df.groupby("class")

In [4]: grouped = df.groupby("order", axis="columns")

In [5]: grouped = df.groupby(["class", "order"])
```

The mapping can be specified many different ways:

- A Python function, to be called on each of the axis labels.
- A list or NumPy array of the same length as the selected axis.
- A dict or `Series`, providing a `label -> group name` mapping.
- For `DataFrame` objects, a string indicating either a column name or an index level name to be used to group.
- `df.groupby('A')` is just syntactic sugar for `df.groupby(df['A'])`.
- A list of any of the above things.

Collectively we refer to the grouping objects as the **keys**. For example, consider the following `DataFrame`:

Note: A string passed to `groupby` may refer to either a column or an index level. If a string matches both a column name and an index level name, a `ValueError` will be raised.

```
In [6]: df = pd.DataFrame(
   ...:     {
   ...:         "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],
   ...:         "B": ["one", "one", "two", "three", "two", "two", "one", "three"],
   ...:         "C": np.random.randn(8),
```

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```
   ...:          "D": np.random.randn(8),
   ...:      }
   ...: )
   ...:

In [7]: df
Out[7]:
     A      B         C         D
0  foo    one  0.469112 -0.861849
1  bar    one -0.282863 -2.104569
2  foo    two -1.509059 -0.494929
3  bar  three -1.135632  1.071804
4  foo    two  1.212112  0.721555
5  bar    two -0.173215 -0.706771
6  foo    one  0.119209 -1.039575
7  foo  three -1.044236  0.271860
```

On a DataFrame, we obtain a GroupBy object by calling *groupby()*. We could naturally group by either the `A` or `B` columns, or both:

```
In [8]: grouped = df.groupby("A")

In [9]: grouped = df.groupby(["A", "B"])
```

New in version 0.24.

If we also have a MultiIndex on columns `A` and `B`, we can group by all but the specified columns

```
In [10]: df2 = df.set_index(["A", "B"])

In [11]: grouped = df2.groupby(level=df2.index.names.difference(["B"]))

In [12]: grouped.sum()
Out[12]:
            C         D
A
bar -1.591710 -1.739537
foo -0.752861 -1.402938
```

These will split the DataFrame on its index (rows). We could also split by the columns:

```
In [13]: def get_letter_type(letter):
   ....:     if letter.lower() in 'aeiou':
   ....:         return 'vowel'
   ....:     else:
   ....:         return 'consonant'
   ....:

In [14]: grouped = df.groupby(get_letter_type, axis=1)
```

pandas *Index* objects support duplicate values. If a non-unique index is used as the group key in a groupby operation, all values for the same index value will be considered to be in one group and thus the output of aggregation functions will only contain unique index values:

```
In [15]: lst = [1, 2, 3, 1, 2, 3]

In [16]: s = pd.Series([1, 2, 3, 10, 20, 30], lst)
```

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```
In [17]: grouped = s.groupby(level=0)

In [18]: grouped.first()
Out[18]:
1    1
2    2
3    3
dtype: int64

In [19]: grouped.last()
Out[19]:
1    10
2    20
3    30
dtype: int64

In [20]: grouped.sum()
Out[20]:
1    11
2    22
3    33
dtype: int64
```

Note that **no splitting occurs** until it's needed. Creating the GroupBy object only verifies that you've passed a valid mapping.

Note: Many kinds of complicated data manipulations can be expressed in terms of GroupBy operations (though can't be guaranteed to be the most efficient). You can get quite creative with the label mapping functions.

GroupBy sorting

By default the group keys are sorted during the `groupby` operation. You may however pass `sort=False` for potential speedups:

```
In [21]: df2 = pd.DataFrame({"X": ["B", "B", "A", "A"], "Y": [1, 2, 3, 4]})

In [22]: df2.groupby(["X"]).sum()
Out[22]:
   Y
X
A  7
B  3

In [23]: df2.groupby(["X"], sort=False).sum()
Out[23]:
   Y
X
B  3
A  7
```

Note that `groupby` will preserve the order in which *observations* are sorted *within* each group. For example, the groups created by `groupby()` below are in the order they appeared in the original `DataFrame`:

```
In [24]: df3 = pd.DataFrame({"X": ["A", "B", "A", "B"], "Y": [1, 4, 3, 2]})

In [25]: df3.groupby(["X"]).get_group("A")
Out[25]:
   X  Y
0  A  1
2  A  3

In [26]: df3.groupby(["X"]).get_group("B")
Out[26]:
   X  Y
1  B  4
3  B  2
```

New in version 1.1.0.

GroupBy dropna

By default `NA` values are excluded from group keys during the `groupby` operation. However, in case you want to include `NA` values in group keys, you could pass `dropna=False` to achieve it.

```
In [27]: df_list = [[1, 2, 3], [1, None, 4], [2, 1, 3], [1, 2, 2]]

In [28]: df_dropna = pd.DataFrame(df_list, columns=["a", "b", "c"])

In [29]: df_dropna
Out[29]:
   a    b  c
0  1  2.0  3
1  1  NaN  4
2  2  1.0  3
3  1  2.0  2
```

```
# Default ``dropna`` is set to True, which will exclude NaNs in keys
In [30]: df_dropna.groupby(by=["b"], dropna=True).sum()
Out[30]:
     a  c
b
1.0  2  3
2.0  2  5

# In order to allow NaN in keys, set ``dropna`` to False
In [31]: df_dropna.groupby(by=["b"], dropna=False).sum()
Out[31]:
     a  c
b
1.0  2  3
2.0  2  5
NaN  1  4
```

The default setting of `dropna` argument is `True` which means `NA` are not included in group keys.

GroupBy object attributes

The `groups` attribute is a dict whose keys are the computed unique groups and corresponding values being the axis labels belonging to each group. In the above example we have:

```
In [32]: df.groupby("A").groups
Out[32]: {'bar': [1, 3, 5], 'foo': [0, 2, 4, 6, 7]}

In [33]: df.groupby(get_letter_type, axis=1).groups
Out[33]: {'consonant': ['B', 'C', 'D'], 'vowel': ['A']}
```

Calling the standard Python `len` function on the GroupBy object just returns the length of the `groups` dict, so it is largely just a convenience:

```
In [34]: grouped = df.groupby(["A", "B"])

In [35]: grouped.groups
Out[35]: {('bar', 'one'): [1], ('bar', 'three'): [3], ('bar', 'two'): [5], ('foo',
↪'one'): [0, 6], ('foo', 'three'): [7], ('foo', 'two'): [2, 4]}

In [36]: len(grouped)
Out[36]: 6
```

`GroupBy` will tab complete column names (and other attributes):

```
In [37]: df
Out[37]:
                height      weight  gender
2000-01-01  42.849980  157.500553    male
2000-01-02  49.607315  177.340407    male
2000-01-03  56.293531  171.524640    male
2000-01-04  48.421077  144.251986  female
2000-01-05  46.556882  152.526206    male
2000-01-06  68.448851  168.272968  female
2000-01-07  70.757698  136.431469    male
2000-01-08  58.909500  176.499753  female
2000-01-09  76.435631  174.094104  female
2000-01-10  45.306120  177.540920    male

In [38]: gb = df.groupby("gender")
```

```
In [39]: gb.<TAB>  # noqa: E225, E999
gb.agg         gb.boxplot     gb.cummin      gb.describe    gb.filter      gb.get_group
↪gb.height     gb.last        gb.median      gb.ngroups     gb.plot        gb.rank
↪gb.std        gb.transform
gb.aggregate   gb.count       gb.cumprod     gb.dtype       gb.first       gb.groups
↪gb.hist       gb.max         gb.min         gb.nth         gb.prod        gb.resample
↪gb.sum        gb.var
gb.apply       gb.cummax      gb.cumsum      gb.fillna      gb.gender      gb.head
↪gb.indices    gb.mean        gb.name        gb.ohlc        gb.quantile    gb.size
↪gb.tail       gb.weight
```

GroupBy with MultiIndex

With *hierarchically-indexed data*, it's quite natural to group by one of the levels of the hierarchy.

Let's create a Series with a two-level `MultiIndex`.

```
In [40]: arrays = [
   ....:     ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
   ....:     ["one", "two", "one", "two", "one", "two", "one", "two"],
   ....: ]
   ....:

In [41]: index = pd.MultiIndex.from_arrays(arrays, names=["first", "second"])

In [42]: s = pd.Series(np.random.randn(8), index=index)

In [43]: s
Out[43]:
first  second
bar    one      -0.919854
       two      -0.042379
baz    one       1.247642
       two      -0.009920
foo    one       0.290213
       two       0.495767
qux    one       0.362949
       two       1.548106
dtype: float64
```

We can then group by one of the levels in `s`.

```
In [44]: grouped = s.groupby(level=0)

In [45]: grouped.sum()
Out[45]:
first
bar   -0.962232
baz    1.237723
foo    0.785980
qux    1.911055
dtype: float64
```

If the MultiIndex has names specified, these can be passed instead of the level number:

```
In [46]: s.groupby(level="second").sum()
Out[46]:
second
one    0.980950
two    1.991575
dtype: float64
```

The aggregation functions such as `sum` will take the level parameter directly. Additionally, the resulting index will be named according to the chosen level:

```
In [47]: s.sum(level="second")
Out[47]:
second
one    0.980950
```

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```
two    1.991575
dtype: float64
```

Grouping with multiple levels is supported.

```
In [48]: s
Out[48]:
first  second  third
bar    doo     one     -1.131345
               two     -0.089329
baz    bee     one      0.337863
               two     -0.945867
foo    bop     one     -0.932132
               two      1.956030
qux    bop     one      0.017587
               two     -0.016692
dtype: float64

In [49]: s.groupby(level=["first", "second"]).sum()
Out[49]:
first  second
bar    doo      -1.220674
baz    bee      -0.608004
foo    bop       1.023898
qux    bop       0.000895
dtype: float64
```

Index level names may be supplied as keys.

```
In [50]: s.groupby(["first", "second"]).sum()
Out[50]:
first  second
bar    doo      -1.220674
baz    bee      -0.608004
foo    bop       1.023898
qux    bop       0.000895
dtype: float64
```

More on the `sum` function and aggregation later.

Grouping DataFrame with Index levels and columns

A DataFrame may be grouped by a combination of columns and index levels by specifying the column names as strings and the index levels as `pd.Grouper` objects.

```
In [51]: arrays = [
   ....:     ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
   ....:     ["one", "two", "one", "two", "one", "two", "one", "two"],
   ....: ]
   ....:

In [52]: index = pd.MultiIndex.from_arrays(arrays, names=["first", "second"])

In [53]: df = pd.DataFrame({"A": [1, 1, 1, 1, 2, 2, 3, 3], "B": np.arange(8)},␣
↪index=index)
```

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```
In [54]: df
Out[54]:
              A  B
first second
bar   one      1  0
      two      1  1
baz   one      1  2
      two      1  3
foo   one      2  4
      two      2  5
qux   one      3  6
      two      3  7
```

The following example groups `df` by the `second` index level and the `A` column.

```
In [55]: df.groupby([pd.Grouper(level=1), "A"]).sum()
Out[55]:
           B
second A
one    1   2
       2   4
       3   6
two    1   4
       2   5
       3   7
```

Index levels may also be specified by name.

```
In [56]: df.groupby([pd.Grouper(level="second"), "A"]).sum()
Out[56]:
           B
second A
one    1   2
       2   4
       3   6
two    1   4
       2   5
       3   7
```

Index level names may be specified as keys directly to `groupby`.

```
In [57]: df.groupby(["second", "A"]).sum()
Out[57]:
           B
second A
one    1   2
       2   4
       3   6
two    1   4
       2   5
       3   7
```

DataFrame column selection in GroupBy

Once you have created the GroupBy object from a DataFrame, you might want to do something different for each of the columns. Thus, using `[]` similar to getting a column from a DataFrame, you can do:

```
In [58]: grouped = df.groupby(["A"])

In [59]: grouped_C = grouped["C"]

In [60]: grouped_D = grouped["D"]
```

This is mainly syntactic sugar for the alternative and much more verbose:

```
In [61]: df["C"].groupby(df["A"])
Out[61]: <pandas.core.groupby.generic.SeriesGroupBy object at 0x7f7110139b50>
```

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

2.17.2 Iterating through groups

With the GroupBy object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby()`:

```
In [62]: grouped = df.groupby('A')

In [63]: for name, group in grouped:
   ....:     print(name)
   ....:     print(group)
   ....:
bar
     A      B         C         D
1  bar    one  0.254161  1.511763
3  bar  three  0.215897 -0.990582
5  bar    two -0.077118  1.211526
foo
     A      B         C         D
0  foo    one -0.575247  1.346061
2  foo    two -1.143704  1.627081
4  foo    two  1.193555 -0.441652
6  foo    one -0.408530  0.268520
7  foo  three -0.862495  0.024580
```

In the case of grouping by multiple keys, the group name will be a tuple:

```
In [64]: for name, group in df.groupby(['A', 'B']):
   ....:     print(name)
   ....:     print(group)
   ....:
('bar', 'one')
     A    B         C         D
1  bar  one  0.254161  1.511763
('bar', 'three')
     A      B         C         D
3  bar  three  0.215897 -0.990582
('bar', 'two')
     A    B         C         D
```

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```
5  bar  two -0.077118  1.211526
('foo', 'one')
     A    B         C         D
0  foo  one -0.575247  1.346061
6  foo  one -0.408530  0.268520
('foo', 'three')
     A      B         C        D
7  foo  three -0.862495  0.02458
('foo', 'two')
     A    B         C         D
2  foo  two -1.143704  1.627081
4  foo  two  1.193555 -0.441652
```

See *Iterating through groups*.

2.17.3 Selecting a group

A single group can be selected using `get_group()`:

```
In [65]: grouped.get_group("bar")
Out[65]:
     A      B         C         D
1  bar    one  0.254161  1.511763
3  bar  three  0.215897 -0.990582
5  bar    two -0.077118  1.211526
```

Or for an object grouped on multiple columns:

```
In [66]: df.groupby(["A", "B"]).get_group(("bar", "one"))
Out[66]:
     A    B         C         D
1  bar  one  0.254161  1.511763
```

2.17.4 Aggregation

Once the GroupBy object has been created, several methods are available to perform a computation on the grouped data. These operations are similar to the *aggregating API*, *window API*, and *resample API*.

An obvious one is aggregation via the *`aggregate()`* or equivalently `agg()` method:

```
In [67]: grouped = df.groupby("A")

In [68]: grouped.aggregate(np.sum)
Out[68]:
            C         D
A
bar  0.392940  1.732707
foo -1.796421  2.824590

In [69]: grouped = df.groupby(["A", "B"])

In [70]: grouped.aggregate(np.sum)
Out[70]:
                  C         D
```

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```
A   B
bar one    0.254161  1.511763
    three  0.215897 -0.990582
    two   -0.077118  1.211526
foo one   -0.983776  1.614581
    three -0.862495  0.024580
    two    0.049851  1.185429
```

As you can see, the result of the aggregation will have the group names as the new index along the grouped axis. In the case of multiple keys, the result is a *MultiIndex* by default, though this can be changed by using the `as_index` option:

```
In [71]: grouped = df.groupby(["A", "B"], as_index=False)

In [72]: grouped.aggregate(np.sum)
Out[72]:
     A      B         C         D
0  bar    one  0.254161  1.511763
1  bar  three  0.215897 -0.990582
2  bar    two -0.077118  1.211526
3  foo    one -0.983776  1.614581
4  foo  three -0.862495  0.024580
5  foo    two  0.049851  1.185429

In [73]: df.groupby("A", as_index=False).sum()
Out[73]:
     A         C         D
0  bar  0.392940  1.732707
1  foo -1.796421  2.824590
```

Note that you could use the `reset_index` DataFrame function to achieve the same result as the column names are stored in the resulting `MultiIndex`:

```
In [74]: df.groupby(["A", "B"]).sum().reset_index()
Out[74]:
     A      B         C         D
0  bar    one  0.254161  1.511763
1  bar  three  0.215897 -0.990582
2  bar    two -0.077118  1.211526
3  foo    one -0.983776  1.614581
4  foo  three -0.862495  0.024580
5  foo    two  0.049851  1.185429
```

Another simple aggregation example is to compute the size of each group. This is included in GroupBy as the `size` method. It returns a Series whose index are the group names and whose values are the sizes of each group.

```
In [75]: grouped.size()
Out[75]:
     A      B  size
0  bar    one     1
1  bar  three     1
2  bar    two     1
3  foo    one     2
4  foo  three     1
5  foo    two     2
```

```
In [76]: grouped.describe()
Out[76]:
      C                                                   ...         D
↪
  count      mean       std       min       25%       50%  ...       std       min
↪    25%       50%       75%       max
0   1.0  0.254161       NaN  0.254161  0.254161  0.254161  ...       NaN  1.511763  1.
↪511763  1.511763  1.511763  1.511763
1   1.0  0.215897       NaN  0.215897  0.215897  0.215897  ...       NaN -0.990582 -0.
↪990582 -0.990582 -0.990582 -0.990582
2   1.0 -0.077118       NaN -0.077118 -0.077118 -0.077118  ...       NaN  1.211526  1.
↪211526  1.211526  1.211526  1.211526
3   2.0 -0.491888  0.117887 -0.575247 -0.533567 -0.491888  ...  0.761937  0.268520  0.
↪537905  0.807291  1.076676  1.346061
4   1.0 -0.862495       NaN -0.862495 -0.862495 -0.862495  ...       NaN  0.024580  0.
↪024580  0.024580  0.024580  0.024580
5   2.0  0.024925  1.652692 -1.143704 -0.559389  0.024925  ...  1.462816 -0.441652  0.
↪075531  0.592714  1.109898  1.627081

[6 rows x 16 columns]
```

Another aggregation example is to compute the number of unique values of each group. This is similar to the `value_counts` function, except that it only counts unique values.

```
In [77]: ll = [['foo', 1], ['foo', 2], ['foo', 2], ['bar', 1], ['bar', 1]]

In [78]: df4 = pd.DataFrame(ll, columns=["A", "B"])

In [79]: df4
Out[79]:
     A  B
0  foo  1
1  foo  2
2  foo  2
3  bar  1
4  bar  1

In [80]: df4.groupby("A")["B"].nunique()
Out[80]:
A
bar    1
foo    2
Name: B, dtype: int64
```

Note: Aggregation functions **will not** return the groups that you are aggregating over if they are named *columns*, when `as_index=True`, the default. The grouped columns will be the **indices** of the returned object.

Passing `as_index=False` **will** return the groups that you are aggregating over, if they are named *columns*.

Aggregating functions are the ones that reduce the dimension of the returned objects. Some common aggregating functions are tabulated below:

Function	Description
mean()	Compute mean of groups
sum()	Compute sum of group values
size()	Compute group sizes
count()	Compute count of group
std()	Standard deviation of groups
var()	Compute variance of groups
sem()	Standard error of the mean of groups
describe()	Generates descriptive statistics
first()	Compute first of group values
last()	Compute last of group values
nth()	Take nth value, or a subset if n is a list
min()	Compute min of group values
max()	Compute max of group values

The aggregating functions above will exclude NA values. Any function which reduces a *Series* to a scalar value is an aggregation function and will work, a trivial example is `df.groupby('A').agg(lambda ser: 1)`. Note that `nth()` can act as a reducer *or* a filter, see *here*.

Applying multiple functions at once

With grouped `Series` you can also pass a list or dict of functions to do aggregation with, outputting a DataFrame:

```
In [81]: grouped = df.groupby("A")

In [82]: grouped["C"].agg([np.sum, np.mean, np.std])
Out[82]:
            sum      mean       std
A
bar  0.392940  0.130980  0.181231
foo -1.796421 -0.359284  0.912265
```

On a grouped `DataFrame`, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [83]: grouped.agg([np.sum, np.mean, np.std])
Out[83]:
            C                              D
          sum      mean       std       sum      mean       std
A
bar  0.392940  0.130980  0.181231  1.732707  0.577569  1.366330
foo -1.796421 -0.359284  0.912265  2.824590  0.564918  0.884785
```

The resulting aggregations are named for the functions themselves. If you need to rename, then you can add in a chained operation for a `Series` like this:

```
In [84]: (
   ....:     grouped["C"]
   ....:     .agg([np.sum, np.mean, np.std])
   ....:     .rename(columns={"sum": "foo", "mean": "bar", "std": "baz"})
   ....: )
   ....:
Out[84]:
          foo       bar       baz
```

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```
A
bar  0.392940  0.130980  0.181231
foo -1.796421 -0.359284  0.912265
```

For a grouped `DataFrame`, you can rename in a similar manner:

```
In [85]: (
   ....:     grouped.agg([np.sum, np.mean, np.std]).rename(
   ....:         columns={"sum": "foo", "mean": "bar", "std": "baz"}
   ....:     )
   ....: )
   ....:
Out[85]:
            C                              D
          foo       bar       baz       foo       bar       baz
A
bar  0.392940  0.130980  0.181231  1.732707  0.577569  1.366330
foo -1.796421 -0.359284  0.912265  2.824590  0.564918  0.884785
```

Note: In general, the output column names should be unique. You can't apply the same function (or two functions with the same name) to the same column.

```
In [86]: grouped["C"].agg(["sum", "sum"])
Out[86]:
          sum       sum
A
bar  0.392940  0.392940
foo -1.796421 -1.796421
```

pandas *does* allow you to provide multiple lambdas. In this case, pandas will mangle the name of the (nameless) lambda functions, appending `_<i>` to each subsequent lambda.

```
In [87]: grouped["C"].agg([lambda x: x.max() - x.min(), lambda x: x.median() - x.
↪mean()])
Out[87]:
     <lambda_0>  <lambda_1>
A
bar    0.331279    0.084917
foo    2.337259   -0.215962
```

Named aggregation

New in version 0.25.0.

To support column-specific aggregation *with control over the output column names*, pandas accepts the special syntax in `GroupBy.agg()`, known as "named aggregation", where

- The keywords are the *output* column names
- The values are tuples whose first element is the column to select and the second element is the aggregation to apply to that column. pandas provides the `pandas.NamedAgg` namedtuple with the fields `['column', 'aggfunc']` to make it clearer what the arguments are. As usual, the aggregation can be a callable or a string alias.

```
In [88]: animals = pd.DataFrame(
   ....:     {
   ....:         "kind": ["cat", "dog", "cat", "dog"],
   ....:         "height": [9.1, 6.0, 9.5, 34.0],
   ....:         "weight": [7.9, 7.5, 9.9, 198.0],
   ....:     }
   ....: )
   ....:

In [89]: animals
Out[89]:
  kind  height  weight
0  cat     9.1     7.9
1  dog     6.0     7.5
2  cat     9.5     9.9
3  dog    34.0   198.0

In [90]: animals.groupby("kind").agg(
   ....:     min_height=pd.NamedAgg(column="height", aggfunc="min"),
   ....:     max_height=pd.NamedAgg(column="height", aggfunc="max"),
   ....:     average_weight=pd.NamedAgg(column="weight", aggfunc=np.mean),
   ....: )
   ....:
Out[90]:
      min_height  max_height  average_weight
kind
cat          9.1         9.5            8.90
dog          6.0        34.0          102.75
```

`pandas.NamedAgg` is just a `namedtuple`. Plain tuples are allowed as well.

```
In [91]: animals.groupby("kind").agg(
   ....:     min_height=("height", "min"),
   ....:     max_height=("height", "max"),
   ....:     average_weight=("weight", np.mean),
   ....: )
   ....:
Out[91]:
      min_height  max_height  average_weight
kind
cat          9.1         9.5            8.90
dog          6.0        34.0          102.75
```

If your desired output column names are not valid Python keywords, construct a dictionary and unpack the keyword arguments

```
In [92]: animals.groupby("kind").agg(
   ....:     **{
   ....:         "total weight": pd.NamedAgg(column="weight", aggfunc=sum)
   ....:     }
   ....: )
   ....:
Out[92]:
      total weight
kind
cat           17.8
dog          205.5
```

Additional keyword arguments are not passed through to the aggregation functions. Only pairs of `(column, aggfunc)` should be passed as `**kwargs`. If your aggregation functions requires additional arguments, partially apply them with `functools.partial()`.

Note: For Python 3.5 and earlier, the order of `**kwargs` in a functions was not preserved. This means that the output column ordering would not be consistent. To ensure consistent ordering, the keys (and so output columns) will always be sorted for Python 3.5.

Named aggregation is also valid for Series groupby aggregations. In this case there's no column selection, so the values are just the functions.

```
In [93]: animals.groupby("kind").height.agg(
   ....:     min_height="min",
   ....:     max_height="max",
   ....: )
   ....:
Out[93]:
      min_height  max_height
kind
cat          9.1         9.5
dog          6.0        34.0
```

Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```
In [94]: grouped.agg({"C": np.sum, "D": lambda x: np.std(x, ddof=1)})
Out[94]:
            C         D
A
bar  0.392940  1.366330
foo -1.796421  0.884785
```

The function names can also be strings. In order for a string to be valid it must be either implemented on GroupBy or available via *dispatching*:

```
In [95]: grouped.agg({"C": "sum", "D": "std"})
Out[95]:
            C         D
A
bar  0.392940  1.366330
foo -1.796421  0.884785
```

Cython-optimized aggregation functions

Some common aggregations, currently only `sum`, `mean`, `std`, and `sem`, have optimized Cython implementations:

```
In [96]: df.groupby("A").sum()
Out[96]:
            C         D
A
bar  0.392940  1.732707
foo -1.796421  2.824590
```

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```
In [97]: df.groupby(["A", "B"]).mean()
Out[97]:
                  C         D
A   B
bar one    0.254161  1.511763
    three  0.215897 -0.990582
    two   -0.077118  1.211526
foo one   -0.491888  0.807291
    three -0.862495  0.024580
    two    0.024925  0.592714
```

Of course `sum` and `mean` are implemented on pandas objects, so the above code would work even without the special versions via dispatching (see below).

2.17.5 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. The transform function must:

- Return a result that is either the same size as the group chunk or broadcastable to the size of the group chunk (e.g., a scalar, `grouped.transform(lambda x: x.iloc[-1])`).
- Operate column-by-column on the group chunk. The transform is applied to the first group chunk using chunk.apply.
- Not perform in-place operations on the group chunk. Group chunks should be treated as immutable, and changes to a group chunk may produce unexpected results. For example, when using `fillna`, `inplace` must be `False` (`grouped.transform(lambda x: x.fillna(inplace=False))`).
- (Optionally) operates on the entire group chunk. If this is supported, a fast path is used starting from the *second* chunk.

For example, suppose we wished to standardize the data within each group:

```
In [98]: index = pd.date_range("10/1/1999", periods=1100)

In [99]: ts = pd.Series(np.random.normal(0.5, 2, 1100), index)

In [100]: ts = ts.rolling(window=100, min_periods=100).mean().dropna()

In [101]: ts.head()
Out[101]:
2000-01-08    0.779333
2000-01-09    0.778852
2000-01-10    0.786476
2000-01-11    0.782797
2000-01-12    0.798110
Freq: D, dtype: float64

In [102]: ts.tail()
Out[102]:
2002-09-30    0.660294
2002-10-01    0.631095
2002-10-02    0.673601
2002-10-03    0.709213
```

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```
2002-10-04    0.719369
Freq: D, dtype: float64

In [103]: transformed = ts.groupby(lambda x: x.year).transform(
   .....:     lambda x: (x - x.mean()) / x.std()
   .....: )
   .....:
```

We would expect the result to now have mean 0 and standard deviation 1 within each group, which we can easily check:

```
# Original Data
In [104]: grouped = ts.groupby(lambda x: x.year)

In [105]: grouped.mean()
Out[105]:
2000    0.442441
2001    0.526246
2002    0.459365
dtype: float64

In [106]: grouped.std()
Out[106]:
2000    0.131752
2001    0.210945
2002    0.128753
dtype: float64

# Transformed Data
In [107]: grouped_trans = transformed.groupby(lambda x: x.year)

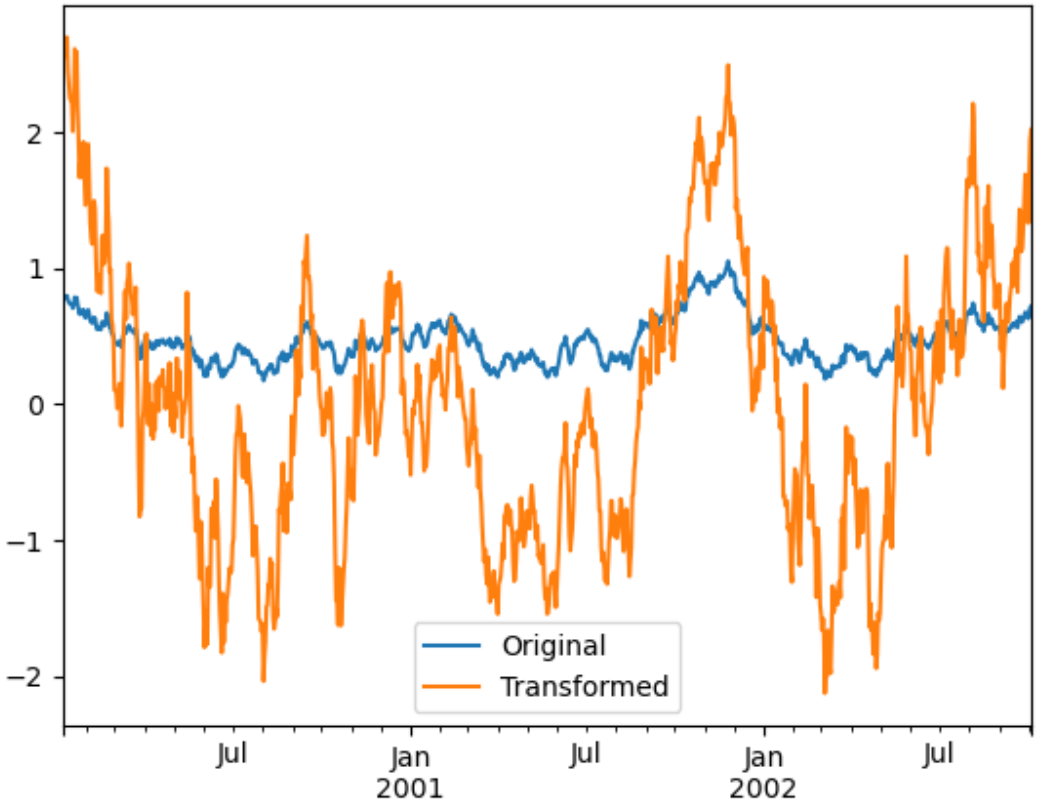
In [108]: grouped_trans.mean()
Out[108]:
2000    1.167126e-15
2001    2.190637e-15
2002    1.088580e-15
dtype: float64

In [109]: grouped_trans.std()
Out[109]:
2000    1.0
2001    1.0
2002    1.0
dtype: float64
```

We can also visually compare the original and transformed data sets.

```
In [110]: compare = pd.DataFrame({"Original": ts, "Transformed": transformed})

In [111]: compare.plot()
Out[111]: <AxesSubplot:>
```



Transformation functions that have lower dimension outputs are broadcast to match the shape of the input array.

```
In [112]: ts.groupby(lambda x: x.year).transform(lambda x: x.max() - x.min())
Out[112]:
2000-01-08    0.623893
2000-01-09    0.623893
2000-01-10    0.623893
2000-01-11    0.623893
2000-01-12    0.623893
                ...
2002-09-30    0.558275
2002-10-01    0.558275
2002-10-02    0.558275
2002-10-03    0.558275
2002-10-04    0.558275
Freq: D, Length: 1001, dtype: float64
```

Alternatively, the built-in methods could be used to produce the same outputs.

```
In [113]: max = ts.groupby(lambda x: x.year).transform("max")

In [114]: min = ts.groupby(lambda x: x.year).transform("min")

In [115]: max - min
Out[115]:
```

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```
2000-01-08    0.623893
2000-01-09    0.623893
2000-01-10    0.623893
2000-01-11    0.623893
2000-01-12    0.623893
                ...
2002-09-30    0.558275
2002-10-01    0.558275
2002-10-02    0.558275
2002-10-03    0.558275
2002-10-04    0.558275
Freq: D, Length: 1001, dtype: float64
```

Another common data transform is to replace missing data with the group mean.

```
In [116]: data_df
Out[116]:
            A         B         C
0    1.539708 -1.166480  0.533026
1    1.302092 -0.505754       NaN
2   -0.371983  1.104803 -0.651520
3   -1.309622  1.118697 -1.161657
4   -1.924296  0.396437  0.812436
..        ...       ...       ...
995 -0.093110  0.683847 -0.774753
996 -0.185043  1.438572       NaN
997 -0.394469 -0.642343  0.011374
998 -1.174126  1.857148       NaN
999  0.234564  0.517098  0.393534

[1000 rows x 3 columns]

In [117]: countries = np.array(["US", "UK", "GR", "JP"])

In [118]: key = countries[np.random.randint(0, 4, 1000)]

In [119]: grouped = data_df.groupby(key)

# Non-NA count in each group
In [120]: grouped.count()
Out[120]:
      A    B    C
GR  209  217  189
JP  240  255  217
UK  216  231  193
US  239  250  217

In [121]: transformed = grouped.transform(lambda x: x.fillna(x.mean()))
```

We can verify that the group means have not changed in the transformed data and that the transformed data contains no NAs.

```
In [122]: grouped_trans = transformed.groupby(key)

In [123]: grouped.mean()  # original group means
Out[123]:
```

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```
           A         B         C
GR -0.098371 -0.015420  0.068053
JP  0.069025  0.023100 -0.077324
UK  0.034069 -0.052580 -0.116525
US  0.058664 -0.020399  0.028603

In [124]: grouped_trans.mean()  # transformation did not change group means
Out[124]:
           A         B         C
GR -0.098371 -0.015420  0.068053
JP  0.069025  0.023100 -0.077324
UK  0.034069 -0.052580 -0.116525
US  0.058664 -0.020399  0.028603

In [125]: grouped.count()  # original has some missing data points
Out[125]:
      A    B    C
GR  209  217  189
JP  240  255  217
UK  216  231  193
US  239  250  217

In [126]: grouped_trans.count()  # counts after transformation
Out[126]:
      A    B    C
GR  228  228  228
JP  267  267  267
UK  247  247  247
US  258  258  258

In [127]: grouped_trans.size()  # Verify non-NA count equals group size
Out[127]:
GR    228
JP    267
UK    247
US    258
dtype: int64
```

Note: Some functions will automatically transform the input when applied to a GroupBy object, but returning an object of the same shape as the original. Passing `as_index=False` will not affect these transformation methods.

For example: `fillna, ffill, bfill, shift..`

```
In [128]: grouped.ffill()
Out[128]:
            A         B         C
0    1.539708 -1.166480  0.533026
1    1.302092 -0.505754  0.533026
2   -0.371983  1.104803 -0.651520
3   -1.309622  1.118697 -1.161657
4   -1.924296  0.396437  0.812436
..        ...       ...       ...
995 -0.093110  0.683847 -0.774753
996 -0.185043  1.438572 -0.774753
997 -0.394469 -0.642343  0.011374
998 -1.174126  1.857148 -0.774753
```

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```
999  0.234564  0.517098  0.393534

[1000 rows x 3 columns]
```

Window and resample operations

It is possible to use `resample()`, `expanding()` and `rolling()` as methods on groupbys.

The example below will apply the `rolling()` method on the samples of the column B based on the groups of column A.

```
In [129]: df_re = pd.DataFrame({"A": [1] * 10 + [5] * 10, "B": np.arange(20)})

In [130]: df_re
Out[130]:
    A   B
0   1   0
1   1   1
2   1   2
3   1   3
4   1   4
..  ..  ..
15  5  15
16  5  16
17  5  17
18  5  18
19  5  19

[20 rows x 2 columns]

In [131]: df_re.groupby("A").rolling(4).B.mean()
Out[131]:
A
1  0      NaN
   1      NaN
   2      NaN
   3      1.5
   4      2.5
         ...
5  15    13.5
   16    14.5
   17    15.5
   18    16.5
   19    17.5
Name: B, Length: 20, dtype: float64
```

The `expanding()` method will accumulate a given operation (`sum()` in the example) for all the members of each particular group.

```
In [132]: df_re.groupby("A").expanding().sum()
Out[132]:
          A      B
A
1 0     1.0    0.0
```

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```
  1    2.0    1.0
  2    3.0    3.0
  3    4.0    6.0
  4    5.0   10.0
...    ...    ...
5 15  30.0   75.0
  16  35.0   91.0
  17  40.0  108.0
  18  45.0  126.0
  19  50.0  145.0

[20 rows x 2 columns]
```

Suppose you want to use the `resample()` method to get a daily frequency in each group of your dataframe and wish to complete the missing values with the `ffill()` method.

```
In [133]: df_re = pd.DataFrame(
   .....:     {
   .....:         "date": pd.date_range(start="2016-01-01", periods=4, freq="W"),
   .....:         "group": [1, 1, 2, 2],
   .....:         "val": [5, 6, 7, 8],
   .....:     }
   ..... ).set_index("date")
   .....:

In [134]: df_re
Out[134]:
            group  val
date
2016-01-03      1    5
2016-01-10      1    6
2016-01-17      2    7
2016-01-24      2    8

In [135]: df_re.groupby("group").resample("1D").ffill()
Out[135]:
                  group  val
group date
1     2016-01-03      1    5
      2016-01-04      1    5
      2016-01-05      1    5
      2016-01-06      1    5
      2016-01-07      1    5
...                 ...  ...
2     2016-01-20      2    7
      2016-01-21      2    7
      2016-01-22      2    7
      2016-01-23      2    7
      2016-01-24      2    8

[16 rows x 2 columns]
```

2.17.6 Filtration

The `filter` method returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [136]: sf = pd.Series([1, 1, 2, 3, 3, 3])

In [137]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[137]:
3    3
4    3
5    3
dtype: int64
```

The argument of `filter` must be a function that, applied to the group as a whole, returns `True` or `False`.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [138]: dff = pd.DataFrame({"A": np.arange(8), "B": list("aabbbbcc")})

In [139]: dff.groupby("B").filter(lambda x: len(x) > 2)
Out[139]:
   A  B
2  2  b
3  3  b
4  4  b
5  5  b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [140]: dff.groupby("B").filter(lambda x: len(x) > 2, dropna=False)
Out[140]:
     A    B
0  NaN  NaN
1  NaN  NaN
2  2.0    b
3  3.0    b
4  4.0    b
5  5.0    b
6  NaN  NaN
7  NaN  NaN
```

For DataFrames with multiple columns, filters should explicitly specify a column as the filter criterion.

```
In [141]: dff["C"] = np.arange(8)

In [142]: dff.groupby("B").filter(lambda x: len(x["C"]) > 2)
Out[142]:
   A  B  C
2  2  b  2
3  3  b  3
4  4  b  4
5  5  b  5
```

Note: Some functions when applied to a groupby object will act as a **filter** on the input, returning a reduced shape of the original (and potentially eliminating groups), but with the index unchanged. Passing `as_index=False` will not

affect these transformation methods.

For example: `head, tail`.

```
In [143]: dff.groupby("B").head(2)
Out[143]:
   A  B  C
0  0  a  0
1  1  a  1
2  2  b  2
3  3  b  3
6  6  c  6
7  7  c  7
```

2.17.7 Dispatching to instance methods

When doing an aggregation or transformation, you might just want to call an instance method on each data group. This is pretty easy to do by passing lambda functions:

```
In [144]: grouped = df.groupby("A")

In [145]: grouped.agg(lambda x: x.std())
Out[145]:
            C         D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

But, it's rather verbose and can be untidy if you need to pass additional arguments. Using a bit of metaprogramming cleverness, GroupBy now has the ability to "dispatch" method calls to the groups:

```
In [146]: grouped.std()
Out[146]:
            C         D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

What is actually happening here is that a function wrapper is being generated. When invoked, it takes any passed arguments and invokes the function with any arguments on each group (in the above example, the `std` function). The results are then combined together much in the style of `agg` and `transform` (it actually uses `apply` to infer the gluing, documented next). This enables some operations to be carried out rather succinctly:

```
In [147]: tsdf = pd.DataFrame(
   .....:     np.random.randn(1000, 3),
   .....:     index=pd.date_range("1/1/2000", periods=1000),
   .....:     columns=["A", "B", "C"],
   .....: )
   .....:

In [148]: tsdf.iloc[::2] = np.nan

In [149]: grouped = tsdf.groupby(lambda x: x.year)

In [150]: grouped.fillna(method="pad")
```

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```
Out[150]:
                   A         B         C
2000-01-01       NaN       NaN       NaN
2000-01-02 -0.353501 -0.080957 -0.876864
2000-01-03 -0.353501 -0.080957 -0.876864
2000-01-04  0.050976  0.044273 -0.559849
2000-01-05  0.050976  0.044273 -0.559849
...              ...       ...       ...
2002-09-22  0.005011  0.053897 -1.026922
2002-09-23  0.005011  0.053897 -1.026922
2002-09-24 -0.456542 -1.849051  1.559856
2002-09-25 -0.456542 -1.849051  1.559856
2002-09-26  1.123162  0.354660  1.128135

[1000 rows x 3 columns]
```

In this example, we chopped the collection of time series into yearly chunks then independently called *fillna* on the groups.

The `nlargest` and `nsmallest` methods work on `Series` style groupbys:

```
In [151]: s = pd.Series([9, 8, 7, 5, 19, 1, 4.2, 3.3])

In [152]: g = pd.Series(list("abababab"))

In [153]: gb = s.groupby(g)

In [154]: gb.nlargest(3)
Out[154]:
a  4    19.0
   0     9.0
   2     7.0
b  1     8.0
   3     5.0
   7     3.3
dtype: float64

In [155]: gb.nsmallest(3)
Out[155]:
a  6    4.2
   2    7.0
   0    9.0
b  5    1.0
   7    3.3
   3    5.0
dtype: float64
```

2.17.8 Flexible `apply`

Some operations on the grouped data might not fit into either the aggregate or transform categories. Or, you may simply want GroupBy to infer how to combine the results. For these, use the `apply` function, which can be substituted for both `aggregate` and `transform` in many standard use cases. However, `apply` can handle some exceptional use cases, for example:

```
In [156]: df
Out[156]:
     A      B         C         D
0  foo    one -0.575247  1.346061
1  bar    one  0.254161  1.511763
2  foo    two -1.143704  1.627081
3  bar  three  0.215897 -0.990582
4  foo    two  1.193555 -0.441652
5  bar    two -0.077118  1.211526
6  foo    one -0.408530  0.268520
7  foo  three -0.862495  0.024580

In [157]: grouped = df.groupby("A")

# could also just call .describe()
In [158]: grouped["C"].apply(lambda x: x.describe())
Out[158]:
A
bar  count    3.000000
     mean     0.130980
     std      0.181231
     min     -0.077118
     25%      0.069390
               ...
foo  min     -1.143704
     25%     -0.862495
     50%     -0.575247
     75%     -0.408530
     max      1.193555
Name: C, Length: 16, dtype: float64
```

The dimension of the returned result can also change:

```
In [159]: grouped = df.groupby('A')['C']

In [160]: def f(group):
   .....:     return pd.DataFrame({'original': group,
   .....:                          'demeaned': group - group.mean()})
   .....:

In [161]: grouped.apply(f)
Out[161]:
   original  demeaned
0 -0.575247 -0.215962
1  0.254161  0.123181
2 -1.143704 -0.784420
3  0.215897  0.084917
4  1.193555  1.552839
5 -0.077118 -0.208098
6 -0.408530 -0.049245
7 -0.862495 -0.503211
```

`apply` on a Series can operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame:

```
In [162]: def f(x):
   .....:     return pd.Series([x, x ** 2], index=["x", "x^2"])
   .....:

In [163]: s = pd.Series(np.random.rand(5))

In [164]: s
Out[164]:
0    0.321438
1    0.493496
2    0.139505
3    0.910103
4    0.194158
dtype: float64

In [165]: s.apply(f)
Out[165]:
          x       x^2
0  0.321438  0.103323
1  0.493496  0.243538
2  0.139505  0.019462
3  0.910103  0.828287
4  0.194158  0.037697
```

Note: `apply` can act as a reducer, transformer, *or* filter function, depending on exactly what is passed to it. So depending on the path taken, and exactly what you are grouping. Thus the grouped columns(s) may be included in the output as well as set the indices.

2.17.9 Numba Accelerated Routines

New in version 1.1.

If Numba is installed as an optional dependency, the `transform` and `aggregate` methods support `engine='numba'` and `engine_kwargs` arguments. The `engine_kwargs` argument is a dictionary of keyword arguments that will be passed into the numba.jit decorator. These keyword arguments will be applied to the passed function. Currently only `nogil`, `nopython`, and `parallel` are supported, and their default values are set to `False`, `True` and `False` respectively.

The function signature must start with `values, index` **exactly** as the data belonging to each group will be passed into `values`, and the group index will be passed into `index`.

Warning: When using `engine='numba'`, there will be no "fall back" behavior internally. The group data and group index will be passed as NumPy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Note: In terms of performance, **the first time a function is run using the Numba engine will be slow** as Numba will have some function compilation overhead. However, the compiled functions are cached, and subsequent calls will be fast. In general, the Numba engine is performant with a larger amount of data points (e.g. 1+ million).

```
In [1]: N = 10 ** 3

In [2]: data = {0: [str(i) for i in range(100)] * N, 1: list(range(100)) * N}

In [3]: df = pd.DataFrame(data, columns=[0, 1])

In [4]: def f_numba(values, index):
   ...:     total = 0
   ...:     for i, value in enumerate(values):
   ...:         if i % 2:
   ...:             total += value + 5
   ...:         else:
   ...:             total += value * 2
   ...:     return total
   ...:

In [5]: def f_cython(values):
   ...:     total = 0
   ...:     for i, value in enumerate(values):
   ...:         if i % 2:
   ...:             total += value + 5
   ...:         else:
   ...:             total += value * 2
   ...:     return total
   ...:

In [6]: groupby = df.groupby(0)
# Run the first time, compilation time will affect performance
In [7]: %timeit -r 1 -n 1 groupby.aggregate(f_numba, engine='numba')  # noqa: E225
2.14 s ± 0 ns per loop (mean ± std. dev. of 1 run, 1 loop each)
# Function is cached and performance will improve
In [8]: %timeit groupby.aggregate(f_numba, engine='numba')
4.93 ms ± 32.3 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [9]: %timeit groupby.aggregate(f_cython, engine='cython')
18.6 ms ± 84.8 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

2.17.10 Other useful features

Automatic exclusion of "nuisance" columns

Again consider the example DataFrame we've been looking at:

```
In [166]: df
Out[166]:
     A      B         C         D
0  foo    one -0.575247  1.346061
1  bar    one  0.254161  1.511763
2  foo    two -1.143704  1.627081
3  bar  three  0.215897 -0.990582
4  foo    two  1.193555 -0.441652
5  bar    two -0.077118  1.211526
6  foo    one -0.408530  0.268520
7  foo  three -0.862495  0.024580
```

Suppose we wish to compute the standard deviation grouped by the `A` column. There is a slight problem, namely that

we don't care about the data in column `B`. We refer to this as a "nuisance" column. If the passed aggregation function can't be applied to some columns, the troublesome columns will be (silently) dropped. Thus, this does not pose any problems:

```
In [167]: df.groupby("A").std()
Out[167]:
            C         D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

Note that `df.groupby('A').colname.std().` is more efficient than `df.groupby('A').std().colname`, so if the result of an aggregation function is only interesting over one column (here `colname`), it may be filtered *before* applying the aggregation function.

Note: Any object column, also if it contains numerical values such as `Decimal` objects, is considered as a "nuisance" columns. They are excluded from aggregate functions automatically in groupby.

If you do wish to include decimal or object columns in an aggregation with other non-nuisance data types, you must do so explicitly.

```
In [168]: from decimal import Decimal

In [169]: df_dec = pd.DataFrame(
   .....:     {
   .....:         "id": [1, 2, 1, 2],
   .....:         "int_column": [1, 2, 3, 4],
   .....:         "dec_column": [
   .....:             Decimal("0.50"),
   .....:             Decimal("0.15"),
   .....:             Decimal("0.25"),
   .....:             Decimal("0.40"),
   .....:         ],
   .....:     }
   ..... )
   .....:

# Decimal columns can be sum'd explicitly by themselves...
In [170]: df_dec.groupby(["id"])[["dec_column"]].sum()
Out[170]:
   dec_column
id
1        0.75
2        0.55

# ...but cannot be combined with standard data types or they will be excluded
In [171]: df_dec.groupby(["id"])[["int_column", "dec_column"]].sum()
Out[171]:
    int_column
id
1            4
2            6

# Use .agg function to aggregate over standard and "nuisance" data types
# at the same time
In [172]: df_dec.groupby(["id"]).agg({"int_column": "sum", "dec_column": "sum"})
```

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```
Out[172]:
    int_column dec_column
id
1            4       0.75
2            6       0.55
```

Handling of (un)observed Categorical values

When using a `Categorical` grouper (as a single grouper, or as part of multiple groupers), the `observed` keyword controls whether to return a cartesian product of all possible groupers values (`observed=False`) or only those that are observed groupers (`observed=True`).

Show all values:

```
In [173]: pd.Series([1, 1, 1]).groupby(
   .....:     pd.Categorical(["a", "a", "a"], categories=["a", "b"]), observed=False
   .....: ).count()
   .....:
Out[173]:
a    3
b    0
dtype: int64
```

Show only the observed values:

```
In [174]: pd.Series([1, 1, 1]).groupby(
   .....:     pd.Categorical(["a", "a", "a"], categories=["a", "b"]), observed=True
   .....: ).count()
   .....:
Out[174]:
a    3
dtype: int64
```

The returned dtype of the grouped will *always* include *all* of the categories that were grouped.

```
In [175]: s = (
   .....:     pd.Series([1, 1, 1])
   .....:     .groupby(pd.Categorical(["a", "a", "a"], categories=["a", "b"]),␣
↪observed=False)
   .....:     .count()
   .....: )
   .....:

In [176]: s.index.dtype
Out[176]: CategoricalDtype(categories=['a', 'b'], ordered=False)
```

NA and NaT group handling

If there are any NaN or NaT values in the grouping key, these will be automatically excluded. In other words, there will never be an "NA group" or "NaT group". This was not the case in older versions of pandas, but users were generally discarding the NA group anyway (and supporting it was an implementation headache).

Grouping with ordered factors

Categorical variables represented as instance of pandas's `Categorical` class can be used as group keys. If so, the order of the levels will be preserved:

```
In [177]: data = pd.Series(np.random.randn(100))

In [178]: factor = pd.qcut(data, [0, 0.25, 0.5, 0.75, 1.0])

In [179]: data.groupby(factor).mean()
Out[179]:
(-2.645, -0.523]   -1.362896
(-0.523, 0.0296]   -0.260266
(0.0296, 0.654]     0.361802
(0.654, 2.21]       1.073801
dtype: float64
```

Grouping with a grouper specification

You may need to specify a bit more data to properly group. You can use the `pd.Grouper` to provide this local control.

```
In [180]: import datetime

In [181]: df = pd.DataFrame(
   .....:     {
   .....:         "Branch": "A A A A A A A B".split(),
   .....:         "Buyer": "Carl Mark Carl Carl Joe Joe Joe Carl".split(),
   .....:         "Quantity": [1, 3, 5, 1, 8, 1, 9, 3],
   .....:         "Date": [
   .....:             datetime.datetime(2013, 1, 1, 13, 0),
   .....:             datetime.datetime(2013, 1, 1, 13, 5),
   .....:             datetime.datetime(2013, 10, 1, 20, 0),
   .....:             datetime.datetime(2013, 10, 2, 10, 0),
   .....:             datetime.datetime(2013, 10, 1, 20, 0),
   .....:             datetime.datetime(2013, 10, 2, 10, 0),
   .....:             datetime.datetime(2013, 12, 2, 12, 0),
   .....:             datetime.datetime(2013, 12, 2, 14, 0),
   .....:         ],
   .....:     }
   .....: )
   .....:

In [182]: df
Out[182]:
  Branch Buyer  Quantity                Date
0      A  Carl         1 2013-01-01 13:00:00
1      A  Mark         3 2013-01-01 13:05:00
2      A  Carl         5 2013-10-01 20:00:00
```

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```
3      A  Carl         1 2013-10-02 10:00:00
4      A   Joe         8 2013-10-01 20:00:00
5      A   Joe         1 2013-10-02 10:00:00
6      A   Joe         9 2013-12-02 12:00:00
7      B  Carl         3 2013-12-02 14:00:00
```

Groupby a specific column with the desired frequency. This is like resampling.

```
In [183]: df.groupby([pd.Grouper(freq="1M", key="Date"), "Buyer"]).sum()
Out[183]:
                  Quantity
Date       Buyer
2013-01-31 Carl          1
           Mark          3
2013-10-31 Carl          6
           Joe           9
2013-12-31 Carl          3
           Joe           9
```

You have an ambiguous specification in that you have a named index and a column that could be potential groupers.

```
In [184]: df = df.set_index("Date")

In [185]: df["Date"] = df.index + pd.offsets.MonthEnd(2)

In [186]: df.groupby([pd.Grouper(freq="6M", key="Date"), "Buyer"]).sum()
Out[186]:
                  Quantity
Date       Buyer
2013-02-28 Carl          1
           Mark          3
2014-02-28 Carl          9
           Joe          18

In [187]: df.groupby([pd.Grouper(freq="6M", level="Date"), "Buyer"]).sum()
Out[187]:
                  Quantity
Date       Buyer
2013-01-31 Carl          1
           Mark          3
2014-01-31 Carl          9
           Joe          18
```

Taking the first rows of each group

Just like for a DataFrame or Series you can call head and tail on a groupby:

```
In [188]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=["A", "B"])

In [189]: df
Out[189]:
   A  B
0  1  2
1  1  4
2  5  6
```

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```
In [190]: g = df.groupby("A")

In [191]: g.head(1)
Out[191]:
   A  B
0  1  2
2  5  6

In [192]: g.tail(1)
Out[192]:
   A  B
1  1  4
2  5  6
```

This shows the first or last n rows from each group.

Taking the nth row of each group

To select from a DataFrame or Series the nth item, use `nth()`. This is a reduction method, and will return a single row (or no row) per group if you pass an int for n:

```
In [193]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=["A", "B"])

In [194]: g = df.groupby("A")

In [195]: g.nth(0)
Out[195]:
     B
A
1  NaN
5  6.0

In [196]: g.nth(-1)
Out[196]:
     B
A
1  4.0
5  6.0

In [197]: g.nth(1)
Out[197]:
     B
A
1  4.0
```

If you want to select the nth not-null item, use the `dropna` kwarg. For a DataFrame this should be either `'any'` or `'all'` just like you would pass to dropna:

```
# nth(0) is the same as g.first()
In [198]: g.nth(0, dropna="any")
Out[198]:
     B
A
1  4.0
```

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```
5  6.0

In [199]: g.first()
Out[199]:
     B
A
1  4.0
5  6.0

# nth(-1) is the same as g.last()
In [200]: g.nth(-1, dropna="any")  # NaNs denote group exhausted when using dropna
Out[200]:
     B
A
1  4.0
5  6.0

In [201]: g.last()
Out[201]:
     B
A
1  4.0
5  6.0

In [202]: g.B.nth(0, dropna="all")
Out[202]:
A
1    4.0
5    6.0
Name: B, dtype: float64
```

As with other methods, passing `as_index=False`, will achieve a filtration, which returns the grouped row.

```
In [203]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=["A", "B"])

In [204]: g = df.groupby("A", as_index=False)

In [205]: g.nth(0)
Out[205]:
   A    B
0  1  NaN
2  5  6.0

In [206]: g.nth(-1)
Out[206]:
   A    B
1  1  4.0
2  5  6.0
```

You can also select multiple rows from each group by specifying multiple nth values as a list of ints.

```
In [207]: business_dates = pd.date_range(start="4/1/2014", end="6/30/2014", freq="B")

In [208]: df = pd.DataFrame(1, index=business_dates, columns=["a", "b"])

# get the first, 4th, and last date index for each month
In [209]: df.groupby([df.index.year, df.index.month]).nth([0, 3, -1])
```

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```
Out[209]:
        a  b
2014 4  1  1
     4  1  1
     4  1  1
     5  1  1
     5  1  1
     5  1  1
     6  1  1
     6  1  1
     6  1  1
```

Enumerate group items

To see the order in which each row appears within its group, use the `cumcount` method:

```
In [210]: dfg = pd.DataFrame(list("aaabba"), columns=["A"])

In [211]: dfg
Out[211]:
   A
0  a
1  a
2  a
3  b
4  b
5  a

In [212]: dfg.groupby("A").cumcount()
Out[212]:
0    0
1    1
2    2
3    0
4    1
5    3
dtype: int64

In [213]: dfg.groupby("A").cumcount(ascending=False)
Out[213]:
0    3
1    2
2    1
3    1
4    0
5    0
dtype: int64
```

Enumerate groups

To see the ordering of the groups (as opposed to the order of rows within a group given by `cumcount`) you can use `ngroup()`.

Note that the numbers given to the groups match the order in which the groups would be seen when iterating over the groupby object, not the order they are first observed.

```
In [214]: dfg = pd.DataFrame(list("aaabba"), columns=["A"])

In [215]: dfg
Out[215]:
   A
0  a
1  a
2  a
3  b
4  b
5  a

In [216]: dfg.groupby("A").ngroup()
Out[216]:
0    0
1    0
2    0
3    1
4    1
5    0
dtype: int64

In [217]: dfg.groupby("A").ngroup(ascending=False)
Out[217]:
0    1
1    1
2    1
3    0
4    0
5    1
dtype: int64
```

Plotting

Groupby also works with some plotting methods. For example, suppose we suspect that some features in a DataFrame may differ by group, in this case, the values in column 1 where the group is “B” are 3 higher on average.

```
In [218]: np.random.seed(1234)

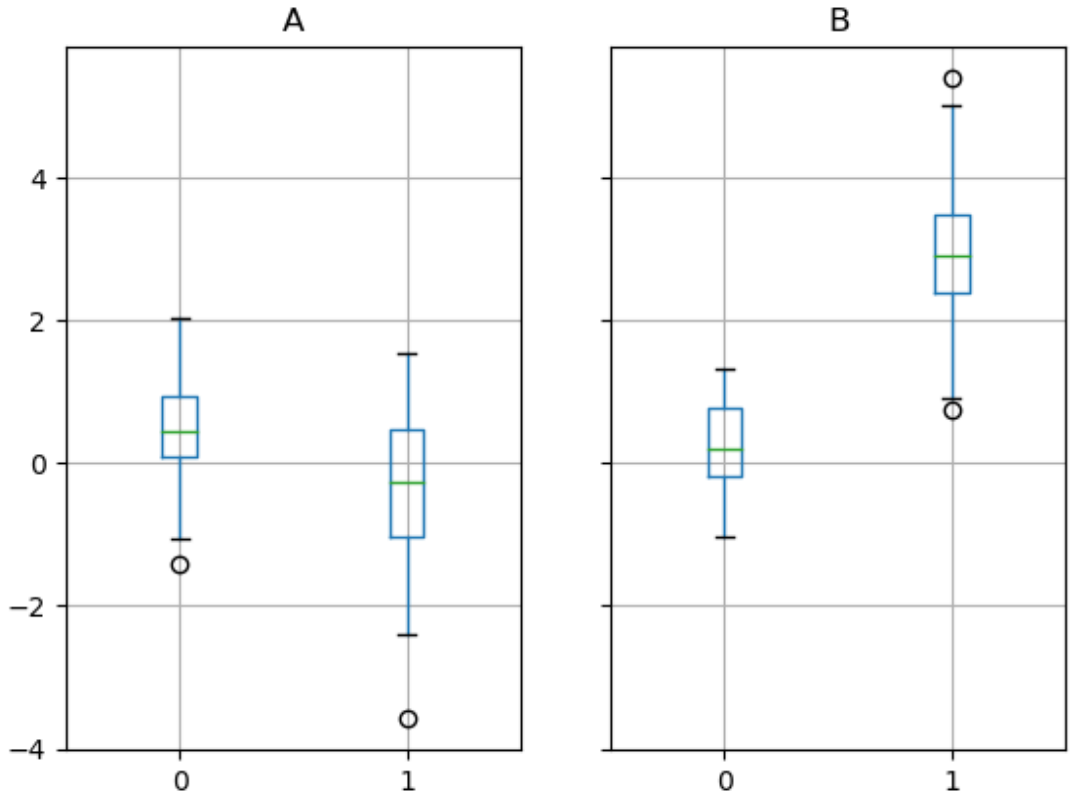
In [219]: df = pd.DataFrame(np.random.randn(50, 2))

In [220]: df["g"] = np.random.choice(["A", "B"], size=50)

In [221]: df.loc[df["g"] == "B", 1] += 3
```

We can easily visualize this with a boxplot:

```
In [222]: df.groupby("g").boxplot()
Out[222]:
A          AxesSubplot(0.1,0.15;0.363636x0.75)
B    AxesSubplot(0.536364,0.15;0.363636x0.75)
dtype: object
```



The result of calling `boxplot` is a dictionary whose keys are the values of our grouping column `g` ("A" and "B"). The values of the resulting dictionary can be controlled by the `return_type` keyword of `boxplot`. See the *visualization documentation* for more.

Warning: For historical reasons, `df.groupby("g").boxplot()` is not equivalent to `df.boxplot(by="g")`. See *here* for an explanation.

Piping function calls

Similar to the functionality provided by `DataFrame` and `Series`, functions that take `GroupBy` objects can be chained together using a `pipe` method to allow for a cleaner, more readable syntax. To read about `.pipe` in general terms, see *here*.

Combining `.groupby` and `.pipe` is often useful when you need to reuse GroupBy objects.

As an example, imagine having a DataFrame with columns for stores, products, revenue and quantity sold. We'd like to do a groupwise calculation of *prices* (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable. First we set the data:

```
In [223]: n = 1000

In [224]: df = pd.DataFrame(
   .....:     {
   .....:         "Store": np.random.choice(["Store_1", "Store_2"], n),
   .....:         "Product": np.random.choice(["Product_1", "Product_2"], n),
   .....:         "Revenue": (np.random.random(n) * 50 + 10).round(2),
   .....:         "Quantity": np.random.randint(1, 10, size=n),
   .....:     }
   .....: )
   .....:

In [225]: df.head(2)
Out[225]:
     Store    Product  Revenue  Quantity
0  Store_2  Product_1    26.12         1
1  Store_2  Product_1    28.86         1
```

Now, to find prices per store/product, we can simply do:

```
In [226]: (
   .....:     df.groupby(["Store", "Product"])
   .....:     .pipe(lambda grp: grp.Revenue.sum() / grp.Quantity.sum())
   .....:     .unstack()
   .....:     .round(2)
   .....: )
   .....:
Out[226]:
Product  Product_1  Product_2
Store
Store_1       6.82       7.05
Store_2       6.30       6.64
```

Piping can also be expressive when you want to deliver a grouped object to some arbitrary function, for example:

```
In [227]: def mean(groupby):
   .....:     return groupby.mean()
   .....:

In [228]: df.groupby(["Store", "Product"]).pipe(mean)
Out[228]:
                     Revenue  Quantity
Store   Product
Store_1 Product_1  34.622727  5.075758
        Product_2  35.482815  5.029630
```

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```
Store_2 Product_1  32.972837  5.237589
        Product_2  34.684360  5.224000
```

where `mean` takes a GroupBy object and finds the mean of the Revenue and Quantity columns respectively for each Store-Product combination. The `mean` function can be any function that takes in a GroupBy object; the `.pipe` will pass the GroupBy object as a parameter into the function you specify.

2.17.11 Examples

Regrouping by factor

Regroup columns of a DataFrame according to their sum, and sum the aggregated ones.

```
In [229]: df = pd.DataFrame({"a": [1, 0, 0], "b": [0, 1, 0], "c": [1, 0, 0], "d": [2,␣
↪3, 4]})

In [230]: df
Out[230]:
   a  b  c  d
0  1  0  1  2
1  0  1  0  3
2  0  0  0  4

In [231]: df.groupby(df.sum(), axis=1).sum()
Out[231]:
   1  9
0  2  2
1  1  3
2  0  4
```

Multi-column factorization

By using `ngroup()`, we can extract information about the groups in a way similar to *`factorize()`* (as described further in the *reshaping API*) but which applies naturally to multiple columns of mixed type and different sources. This can be useful as an intermediate categorical-like step in processing, when the relationships between the group rows are more important than their content, or as input to an algorithm which only accepts the integer encoding. (For more information about support in pandas for full categorical data, see the *Categorical introduction* and the *API documentation*.)

```
In [232]: dfg = pd.DataFrame({"A": [1, 1, 2, 3, 2], "B": list("aaaba")})

In [233]: dfg
Out[233]:
   A  B
0  1  a
1  1  a
2  2  a
3  3  b
4  2  a

In [234]: dfg.groupby(["A", "B"]).ngroup()
Out[234]:
0    0
```

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```
1    0
2    1
3    2
4    1
dtype: int64

In [235]: dfg.groupby(["A", [0, 0, 0, 1, 1]]).ngroup()
Out[235]:
0    0
1    0
2    1
3    3
4    2
dtype: int64
```

Groupby by indexer to 'resample' data

Resampling produces new hypothetical samples (resamples) from already existing observed data or from a model that generates data. These new samples are similar to the pre-existing samples.

In order to resample to work on indices that are non-datetimelike, the following procedure can be utilized.

In the following examples, **df.index // 5** returns a binary array which is used to determine what gets selected for the groupby operation.

Note: The below example shows how we can downsample by consolidation of samples into fewer samples. Here by using **df.index // 5**, we are aggregating the samples in bins. By applying **std()** function, we aggregate the information contained in many samples into a small subset of values which is their standard deviation thereby reducing the number of samples.

```
In [236]: df = pd.DataFrame(np.random.randn(10, 2))

In [237]: df
Out[237]:
          0         1
0 -0.793893  0.321153
1  0.342250  1.618906
2 -0.975807  1.918201
3 -0.810847 -1.405919
4 -1.977759  0.461659
5  0.730057 -1.316938
6 -0.751328  0.528290
7 -0.257759 -1.081009
8  0.505895 -1.701948
9 -1.006349  0.020208

In [238]: df.index // 5
Out[238]: Int64Index([0, 0, 0, 0, 0, 1, 1, 1, 1, 1], dtype='int64')

In [239]: df.groupby(df.index // 5).std()
Out[239]:
          0         1
0  0.823647  1.312912
1  0.760109  0.942941
```

Returning a Series to propagate names

Group DataFrame columns, compute a set of metrics and return a named Series. The Series name is used as the name for the column index. This is especially useful in conjunction with reshaping operations such as stacking in which the column index name will be used as the name of the inserted column:

```
In [240]: df = pd.DataFrame(
   .....:     {
   .....:         "a": [0, 0, 0, 0, 1, 1, 1, 1, 2, 2, 2, 2],
   .....:         "b": [0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1],
   .....:         "c": [1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0],
   .....:         "d": [0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1],
   .....:     }
   .....: )
   .....:

In [241]: def compute_metrics(x):
   .....:     result = {"b_sum": x["b"].sum(), "c_mean": x["c"].mean()}
   .....:     return pd.Series(result, name="metrics")
   .....:

In [242]: result = df.groupby("a").apply(compute_metrics)

In [243]: result
Out[243]:
metrics  b_sum  c_mean
a
0          2.0     0.5
1          2.0     0.5
2          2.0     0.5

In [244]: result.stack()
Out[244]:
a  metrics
0  b_sum      2.0
   c_mean     0.5
1  b_sum      2.0
   c_mean     0.5
2  b_sum      2.0
   c_mean     0.5
dtype: float64
```

2.18 Windowing Operations

pandas contains a compact set of APIs for performing windowing operations - an operation that performs an aggregation over a sliding partition of values. The API functions similarly to the `groupby` API in that *`Series`* and *`DataFrame`* call the windowing method with necessary parameters and then subsequently call the aggregation function.

```
In [1]: s = pd.Series(range(5))

In [2]: s.rolling(window=2).sum()
Out[2]:
0    NaN
1    1.0
```

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```
2    3.0
3    5.0
4    7.0
dtype: float64
```

The windows are comprised by looking back the length of the window from the current observation. The result above can be derived by taking the sum of the following windowed partitions of data:

```
In [3]: for window in s.rolling(window=2):
   ...:     print(window)
   ...:
0    0
dtype: int64
0    0
1    1
dtype: int64
1    1
2    2
dtype: int64
2    2
3    3
dtype: int64
3    3
4    4
dtype: int64
```

2.18.1 Overview

pandas supports 4 types of windowing operations:

1. Rolling window: Generic fixed or variable sliding window over the values.
2. Weighted window: Weighted, non-rectangular window supplied by the `scipy.signal` library.
3. Expanding window: Accumulating window over the values.
4. Exponentially Weighted window: Accumulating and exponentially weighted window over the values.

Concept	Method	Returned Object	Supports time-based windows	Supports chained groupby
Rolling window	`rolling`	`Rolling`	Yes	Yes
Weighted window	`rolling`	`Window`	No	No
Expanding window	`expanding`	`Expanding`	No	Yes
Exponentially Weighted window	`ewm`	`ExponentialMovingWindow`	No	Yes (as of version 1.2)

As noted above, some operations support specifying a window based on a time offset:

```
In [4]: s = pd.Series(range(5), index=pd.date_range('2020-01-01', periods=5, freq='1D
↪'))

In [5]: s.rolling(window='2D').sum()
Out[5]:
2020-01-01    0.0
2020-01-02    1.0
```

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```
2020-01-03    3.0
2020-01-04    5.0
2020-01-05    7.0
Freq: D, dtype: float64
```

Additionally, some methods support chaining a `groupby` operation with a windowing operation which will first group the data by the specified keys and then perform a windowing operation per group.

```
In [6]: df = pd.DataFrame({'A': ['a', 'b', 'a', 'b', 'a'], 'B': range(5)})

In [7]: df.groupby('A').expanding().sum()
Out[7]:
       B
A
a 0  0.0
  2  2.0
  4  6.0
b 1  1.0
  3  4.0
```

Note: Windowing operations currently only support numeric data (integer and float) and will always return `float64` values.

Warning: Some windowing aggregation, `mean`, `sum`, `var` and `std` methods may suffer from numerical imprecision due to the underlying windowing algorithms accumulating sums. When values differ with magnitude $1/np.finfo(np.double).eps$ this results in truncation. It must be noted, that large values may have an impact on windows, which do not include these values. Kahan summation is used to compute the rolling sums to preserve accuracy as much as possible.

All windowing operations support a `min_periods` argument that dictates the minimum amount of non-`np.nan` values a window must have; otherwise, the resulting value is `np.nan`. `min_peridos` defaults to 1 for time-based windows and `window` for fixed windows

```
In [8]: s = pd.Series([np.nan, 1, 2, np.nan, np.nan, 3])

In [9]: s.rolling(window=3, min_periods=1).sum()
Out[9]:
0    NaN
1    1.0
2    3.0
3    3.0
4    2.0
5    3.0
dtype: float64

In [10]: s.rolling(window=3, min_periods=2).sum()
Out[10]:
0    NaN
1    NaN
2    3.0
3    3.0
4    NaN
```

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```
5    NaN
dtype: float64

# Equivalent to min_periods=3
In [11]: s.rolling(window=3, min_periods=None).sum()
Out[11]:
0   NaN
1   NaN
2   NaN
3   NaN
4   NaN
5   NaN
dtype: float64
```

Additionally, all windowing operations supports the `aggregate` method for returning a result of multiple aggregations applied to a window.

```
In [12]: df = pd.DataFrame({"A": range(5), "B": range(10, 15)})

In [13]: df.expanding().agg([np.sum, np.mean, np.std])
Out[13]:
      A                    B
    sum mean       std    sum  mean       std
0   0.0  0.0       NaN  10.0  10.0       NaN
1   1.0  0.5  0.707107  21.0  10.5  0.707107
2   3.0  1.0  1.000000  33.0  11.0  1.000000
3   6.0  1.5  1.290994  46.0  11.5  1.290994
4  10.0  2.0  1.581139  60.0  12.0  1.581139
```

2.18.2 Rolling window

Generic rolling windows support specifying windows as a fixed number of observations or variable number of observations based on an offset. If a time based offset is provided, the corresponding time based index must be monotonic.

```
In [14]: times = ['2020-01-01', '2020-01-03', '2020-01-04', '2020-01-05', '2020-01-29
↪']

In [15]: s = pd.Series(range(5), index=pd.DatetimeIndex(times))

In [16]: s
Out[16]:
2020-01-01    0
2020-01-03    1
2020-01-04    2
2020-01-05    3
2020-01-29    4
dtype: int64

# Window with 2 observations
In [17]: s.rolling(window=2).sum()
Out[17]:
2020-01-01    NaN
2020-01-03    1.0
2020-01-04    3.0
2020-01-05    5.0
```

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```
2020-01-29    7.0
dtype: float64

# Window with 2 days worth of observations
In [18]: s.rolling(window='2D').sum()
Out[18]:
2020-01-01    0.0
2020-01-03    1.0
2020-01-04    3.0
2020-01-05    5.0
2020-01-29    4.0
dtype: float64
```

For all supported aggregation functions, see *Rolling window functions*.

Centering windows

By default the labels are set to the right edge of the window, but a `center` keyword is available so the labels can be set at the center.

```
In [19]: s = pd.Series(range(10))

In [20]: s.rolling(window=5).mean()
Out[20]:
0    NaN
1    NaN
2    NaN
3    NaN
4    2.0
5    3.0
6    4.0
7    5.0
8    6.0
9    7.0
dtype: float64

In [21]: s.rolling(window=5, center=True).mean()
Out[21]:
0    NaN
1    NaN
2    2.0
3    3.0
4    4.0
5    5.0
6    6.0
7    7.0
8    NaN
9    NaN
dtype: float64
```

Rolling window endpoints

The inclusion of the interval endpoints in rolling window calculations can be specified with the `closed` parameter:

Value	Behavior
`right'`	close right endpoint
`'left'`	close left endpoint
`'both'`	close both endpoints
`'neither'`	open endpoints

For example, having the right endpoint open is useful in many problems that require that there is no contamination from present information back to past information. This allows the rolling window to compute statistics "up to that point in time", but not including that point in time.

```
In [22]: df = pd.DataFrame(
   ....:     {"x": 1},
   ....:     index=[
   ....:         pd.Timestamp("20130101 09:00:01"),
   ....:         pd.Timestamp("20130101 09:00:02"),
   ....:         pd.Timestamp("20130101 09:00:03"),
   ....:         pd.Timestamp("20130101 09:00:04"),
   ....:         pd.Timestamp("20130101 09:00:06"),
   ....:     ],
   ....: )
   ....:

In [23]: df["right"] = df.rolling("2s", closed="right").x.sum()  # default

In [24]: df["both"] = df.rolling("2s", closed="both").x.sum()

In [25]: df["left"] = df.rolling("2s", closed="left").x.sum()

In [26]: df["neither"] = df.rolling("2s", closed="neither").x.sum()

In [27]: df
Out[27]:
                     x  right  both  left  neither
2013-01-01 09:00:01  1    1.0   1.0   NaN      NaN
2013-01-01 09:00:02  1    2.0   2.0   1.0      1.0
2013-01-01 09:00:03  1    2.0   3.0   2.0      1.0
2013-01-01 09:00:04  1    2.0   3.0   2.0      1.0
2013-01-01 09:00:06  1    1.0   2.0   1.0      NaN
```

Custom window rolling

New in version 1.0.

In addition to accepting an integer or offset as a `window` argument, `rolling` also accepts a `BaseIndexer` subclass that allows a user to define a custom method for calculating window bounds. The `BaseIndexer` subclass will need to define a `get_window_bounds` method that returns a tuple of two arrays, the first being the starting indices of the windows and second being the ending indices of the windows. Additionally, `num_values`, `min_periods`, `center`, `closed` and will automatically be passed to `get_window_bounds` and the defined method must always accept these arguments.

For example, if we have the following :class:`DataFrame`:

```
In [28]: use_expanding = [True, False, True, False, True]

In [29]: use_expanding
Out[29]: [True, False, True, False, True]

In [30]: df = pd.DataFrame({"values": range(5)})

In [31]: df
Out[31]:
   values
0       0
1       1
2       2
3       3
4       4
```

and we want to use an expanding window where `use_expanding` is `True` otherwise a window of size 1, we can create the following `BaseIndexer` subclass:

```
In [2]: from pandas.api.indexers import BaseIndexer
...:
...: class CustomIndexer(BaseIndexer):
...:
...:     def get_window_bounds(self, num_values, min_periods, center, closed):
...:         start = np.empty(num_values, dtype=np.int64)
...:         end = np.empty(num_values, dtype=np.int64)
...:         for i in range(num_values):
...:             if self.use_expanding[i]:
...:                 start[i] = 0
...:                 end[i] = i + 1
...:             else:
...:                 start[i] = i
...:                 end[i] = i + self.window_size
...:         return start, end
...:

In [3]: indexer = CustomIndexer(window_size=1, use_expanding=use_expanding)

In [4]: df.rolling(indexer).sum()
Out[4]:
    values
0      0.0
1      1.0
2      3.0
3      3.0
4     10.0
```

You can view other examples of `BaseIndexer` subclasses here

New in version 1.1.

One subclass of note within those examples is the `VariableOffsetWindowIndexer` that allows rolling operations over a non-fixed offset like a `BusinessDay`.

```
In [32]: from pandas.api.indexers import VariableOffsetWindowIndexer

In [33]: df = pd.DataFrame(range(10), index=pd.date_range("2020", periods=10))
```

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```
In [34]: offset = pd.offsets.BDay(1)

In [35]: indexer = VariableOffsetWindowIndexer(index=df.index, offset=offset)

In [36]: df
Out[36]:
                0
2020-01-01  0
2020-01-02  1
2020-01-03  2
2020-01-04  3
2020-01-05  4
2020-01-06  5
2020-01-07  6
2020-01-08  7
2020-01-09  8
2020-01-10  9

In [37]: df.rolling(indexer).sum()
Out[37]:
                 0
2020-01-01   0.0
2020-01-02   1.0
2020-01-03   2.0
2020-01-04   3.0
2020-01-05   7.0
2020-01-06  12.0
2020-01-07   6.0
2020-01-08   7.0
2020-01-09   8.0
2020-01-10   9.0
```

For some problems knowledge of the future is available for analysis. For example, this occurs when each data point is a full time series read from an experiment, and the task is to extract underlying conditions. In these cases it can be useful to perform forward-looking rolling window computations. *FixedForwardWindowIndexer* class is available for this purpose. This *BaseIndexer* subclass implements a closed fixed-width forward-looking rolling window, and we can use it as follows:

Rolling apply

The `apply()` function takes an extra `func` argument and performs generic rolling computations. The `func` argument should be a single function that produces a single value from an ndarray input. `raw` specifies whether the windows are cast as *Series* objects (`raw=False`) or ndarray objects (`raw=True`).

```
In [38]: def mad(x):
   ....:     return np.fabs(x - x.mean()).mean()
   ....:

In [39]: s = pd.Series(range(10))

In [40]: s.rolling(window=4).apply(mad, raw=True)
Out[40]:
0    NaN
1    NaN
2    NaN
```

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```
3    1.0
4    1.0
5    1.0
6    1.0
7    1.0
8    1.0
9    1.0
dtype: float64
```

Numba engine

New in version 1.0.

Additionally, `apply()` can leverage Numba if installed as an optional dependency. The apply aggregation can be executed using Numba by specifying `engine='numba'` and `engine_kwargs` arguments (`raw` must also be set to `True`). Numba will be applied in potentially two routines:

1. If `func` is a standard Python function, the engine will JIT the passed function. `func` can also be a JITed function in which case the engine will not JIT the function again.
2. The engine will JIT the for loop where the apply function is applied to each window.

The `engine_kwargs` argument is a dictionary of keyword arguments that will be passed into the numba.jit decorator. These keyword arguments will be applied to *both* the passed function (if a standard Python function) and the apply for loop over each window. Currently only `nogil`, `nopython`, and `parallel` are supported, and their default values are set to `False`, `True` and `False` respectively.

Note: In terms of performance, **the first time a function is run using the Numba engine will be slow** as Numba will have some function compilation overhead. However, the compiled functions are cached, and subsequent calls will be fast. In general, the Numba engine is performant with a larger amount of data points (e.g. 1+ million).

```
In [1]: data = pd.Series(range(1_000_000))

In [2]: roll = data.rolling(10)

In [3]: def f(x):
   ...:     return np.sum(x) + 5
# Run the first time, compilation time will affect performance
In [4]: %timeit -r 1 -n 1 roll.apply(f, engine='numba', raw=True)  # noqa: E225, E999
1.23 s ± 0 ns per loop (mean ± std. dev. of 1 run, 1 loop each)
# Function is cached and performance will improve
In [5]: %timeit roll.apply(f, engine='numba', raw=True)
188 ms ± 1.93 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [6]: %timeit roll.apply(f, engine='cython', raw=True)
3.92 s ± 59 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Binary window functions

`cov()` and `corr()` can compute moving window statistics about two *Series* or any combination of *DataFrame*/*Series* or *DataFrame*/*DataFrame*. Here is the behavior in each case:

- two *Series*: compute the statistic for the pairing.
- *DataFrame*/*Series*: compute the statistics for each column of the DataFrame with the passed Series, thus returning a DataFrame.
- *DataFrame*/*DataFrame*: by default compute the statistic for matching column names, returning a DataFrame. If the keyword argument `pairwise=True` is passed then computes the statistic for each pair of columns, returning a `MultiIndexed DataFrame` whose `index` are the dates in question (see *the next section*).

For example:

```
In [41]: df = pd.DataFrame(
   ....:     np.random.randn(10, 4),
   ....:     index=pd.date_range("2020-01-01", periods=10),
   ....:     columns=["A", "B", "C", "D"],
   ....: )
   ....:

In [42]: df = df.cumsum()

In [43]: df2 = df[:4]

In [44]: df2.rolling(window=2).corr(df2["B"])
Out[44]:
                A    B    C    D
2020-01-01  NaN  NaN  NaN  NaN
2020-01-02 -1.0  1.0 -1.0  1.0
2020-01-03  1.0  1.0  1.0 -1.0
2020-01-04 -1.0  1.0  1.0 -1.0
```

Computing rolling pairwise covariances and correlations

In financial data analysis and other fields it's common to compute covariance and correlation matrices for a collection of time series. Often one is also interested in moving-window covariance and correlation matrices. This can be done by passing the `pairwise` keyword argument, which in the case of *DataFrame* inputs will yield a MultiIndexed *DataFrame* whose `index` are the dates in question. In the case of a single DataFrame argument the `pairwise` argument can even be omitted:

Note: Missing values are ignored and each entry is computed using the pairwise complete observations. Please see the *covariance section* for *caveats* associated with this method of calculating covariance and correlation matrices.

```
In [45]: covs = (
   ....:     df[["B", "C", "D"]]
   ....:     .rolling(window=4)
   ....:     .cov(df[["A", "B", "C"]], pairwise=True)
   ....: )
   ....:

In [46]: covs
```

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```
Out[46]:
                     B         C         D
2020-01-01 A       NaN       NaN       NaN
           B       NaN       NaN       NaN
           C       NaN       NaN       NaN
2020-01-02 A       NaN       NaN       NaN
           B       NaN       NaN       NaN
...                ...       ...       ...
2020-01-09 B  0.342006  0.230190  0.052849
           C  0.230190  1.575251  0.082901
2020-01-10 A -0.333945  0.006871 -0.655514
           B  0.649711  0.430860  0.469271
           C  0.430860  0.829721  0.055300

[30 rows x 3 columns]
```

2.18.3 Weighted window

The `win_type` argument in `.rolling` generates a weighted windows that are commonly used in filtering and spectral estimation. `win_type` must be string that corresponds to a scipy.signal window function. Scipy must be installed in order to use these windows, and supplementary arguments that the Scipy window methods take must be specified in the aggregation function.

```
In [47]: s = pd.Series(range(10))

In [48]: s.rolling(window=5).mean()
Out[48]:
0    NaN
1    NaN
2    NaN
3    NaN
4    2.0
5    3.0
6    4.0
7    5.0
8    6.0
9    7.0
dtype: float64

In [49]: s.rolling(window=5, win_type="triang").mean()
Out[49]:
0    NaN
1    NaN
2    NaN
3    NaN
4    2.0
5    3.0
6    4.0
7    5.0
8    6.0
9    7.0
dtype: float64

# Supplementary Scipy arguments passed in the aggregation function
In [50]: s.rolling(window=5, win_type="gaussian").mean(std=0.1)
```

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```
Out[50]:
0    NaN
1    NaN
2    NaN
3    NaN
4    2.0
5    3.0
6    4.0
7    5.0
8    6.0
9    7.0
dtype: float64
```

For all supported aggregation functions, see *Weighted window functions*.

2.18.4 Expanding window

An expanding window yields the value of an aggregation statistic with all the data available up to that point in time. Since these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```
In [51]: df = pd.DataFrame(range(5))

In [52]: df.rolling(window=len(df), min_periods=1).mean()
Out[52]:
     0
0  0.0
1  0.5
2  1.0
3  1.5
4  2.0

In [53]: df.expanding(min_periods=1).mean()
Out[53]:
     0
0  0.0
1  0.5
2  1.0
3  1.5
4  2.0
```

For all supported aggregation functions, see *Expanding window functions*.

2.18.5 Exponentially Weighted window

An exponentially weighted window is similar to an expanding window but with each prior point being exponentially weighted down relative to the current point.

In general, a weighted moving average is calculated as

$$y_t = \frac{\sum_{i=0}^{t} w_i x_{t-i}}{\sum_{i=0}^{t} w_i},$$

where x_t is the input, y_t is the result and the w_i are the weights.

For all supported aggregation functions, see *Exponentially-weighted window functions*.

The EW functions support two variants of exponential weights. The default, `adjust=True`, uses the weights $w_i = (1-\alpha)^i$ which gives

$$y_t = \frac{x_t + (1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + ... + (1-\alpha)^t x_0}{1 + (1-\alpha) + (1-\alpha)^2 + ... + (1-\alpha)^t}$$

When `adjust=False` is specified, moving averages are calculated as

$$\begin{aligned} y_0 &= x_0 \\ y_t &= (1-\alpha)y_{t-1} + \alpha x_t, \end{aligned}$$

which is equivalent to using weights

$$w_i = \begin{cases} \alpha(1-\alpha)^i & \text{if } i < t \\ (1-\alpha)^i & \text{if } i = t. \end{cases}$$

Note: These equations are sometimes written in terms of $\alpha' = 1 - \alpha$, e.g.

$$y_t = \alpha' y_{t-1} + (1-\alpha')x_t.$$

The difference between the above two variants arises because we are dealing with series which have finite history. Consider a series of infinite history, with `adjust=True`:

$$y_t = \frac{x_t + (1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + ...}{1 + (1-\alpha) + (1-\alpha)^2 + ...}$$

Noting that the denominator is a geometric series with initial term equal to 1 and a ratio of $1-\alpha$ we have

$$\begin{aligned} y_t &= \frac{x_t + (1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + ...}{\frac{1}{1-(1-\alpha)}} \\ &= [x_t + (1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + ...]\alpha \\ &= \alpha x_t + [(1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + ...]\alpha \\ &= \alpha x_t + (1-\alpha)[x_{t-1} + (1-\alpha)x_{t-2} + ...]\alpha \\ &= \alpha x_t + (1-\alpha)y_{t-1} \end{aligned}$$

which is the same expression as `adjust=False` above and therefore shows the equivalence of the two variants for infinite series. When `adjust=False`, we have $y_0 = x_0$ and $y_t = \alpha x_t + (1-\alpha)y_{t-1}$. Therefore, there is an assumption that x_0 is not an ordinary value but rather an exponentially weighted moment of the infinite series up to that point.

One must have $0 < \alpha \leq 1$, and while it is possible to pass α directly, it's often easier to think about either the **span**, **center of mass (com)** or **half-life** of an EW moment:

$$\alpha = \begin{cases} \frac{2}{s+1}, & \text{for span } s \geq 1 \\ \frac{1}{1+c}, & \text{for center of mass } c \geq 0 \\ 1 - \exp^{\frac{\log 0.5}{h}}, & \text{for half-life } h > 0 \end{cases}$$

One must specify precisely one of **span**, **center of mass**, **half-life** and **alpha** to the EW functions:

- **Span** corresponds to what is commonly called an "N-day EW moving average".
- **Center of mass** has a more physical interpretation and can be thought of in terms of span: $c = (s-1)/2$.

- **Half-life** is the period of time for the exponential weight to reduce to one half.
- **Alpha** specifies the smoothing factor directly.

New in version 1.1.0.

You can also specify `halflife` in terms of a timedelta convertible unit to specify the amount of time it takes for an observation to decay to half its value when also specifying a sequence of `times`.

```
In [54]: df = pd.DataFrame({"B": [0, 1, 2, np.nan, 4]})

In [55]: df
Out[55]:
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0

In [56]: times = ["2020-01-01", "2020-01-03", "2020-01-10", "2020-01-15", "2020-01-17
↪"]

In [57]: df.ewm(halflife="4 days", times=pd.DatetimeIndex(times)).mean()
Out[57]:
          B
0  0.000000
1  0.585786
2  1.523889
3  1.523889
4  3.233686
```

The following formula is used to compute exponentially weighted mean with an input vector of times:

$$y_t = \frac{\sum_{i=0}^{t} 0.5^{\frac{t_t - t_i}{\lambda}} x_{t-i}}{0.5^{\frac{t_t - t_i}{\lambda}}},$$

ExponentialMovingWindow also has an `ignore_na` argument, which determines how intermediate null values affect the calculation of the weights. When `ignore_na=False` (the default), weights are calculated based on absolute positions, so that intermediate null values affect the result. When `ignore_na=True`, weights are calculated by ignoring intermediate null values. For example, assuming `adjust=True`, if `ignore_na=False`, the weighted average of `3, NaN, 5` would be calculated as

$$\frac{(1-\alpha)^2 \cdot 3 + 1 \cdot 5}{(1-\alpha)^2 + 1}.$$

Whereas if `ignore_na=True`, the weighted average would be calculated as

$$\frac{(1-\alpha) \cdot 3 + 1 \cdot 5}{(1-\alpha) + 1}.$$

The `var()`, `std()`, and `cov()` functions have a `bias` argument, specifying whether the result should contain biased or unbiased statistics. For example, if `bias=True`, `ewmvar(x)` is calculated as `ewmvar(x) = ewma(x**2) - ewma(x)**2`; whereas if `bias=False` (the default), the biased variance statistics are scaled by debiasing factors

$$\frac{\left(\sum_{i=0}^{t} w_i\right)^2}{\left(\sum_{i=0}^{t} w_i\right)^2 - \sum_{i=0}^{t} w_i^2}.$$

(For $w_i = 1$, this reduces to the usual $N/(N-1)$ factor, with $N = t+1$.) See Weighted Sample Variance on Wikipedia for further details.

2.19 Time series / date functionality

pandas contains extensive capabilities and features for working with time series data for all domains. Using the NumPy `datetime64` and `timedelta64` dtypes, pandas has consolidated a large number of features from other Python libraries like `scikits.timeseries` as well as created a tremendous amount of new functionality for manipulating time series data.

For example, pandas supports:

Parsing time series information from various sources and formats

```
In [1]: import datetime

In [2]: dti = pd.to_datetime(
   ...:     ["1/1/2018", np.datetime64("2018-01-01"), datetime.datetime(2018, 1, 1)]
   ...: )
   ...:

In [3]: dti
Out[3]: DatetimeIndex(['2018-01-01', '2018-01-01', '2018-01-01'], dtype=
↪'datetime64[ns]', freq=None)
```

Generate sequences of fixed-frequency dates and time spans

```
In [4]: dti = pd.date_range("2018-01-01", periods=3, freq="H")

In [5]: dti
Out[5]:
DatetimeIndex(['2018-01-01 00:00:00', '2018-01-01 01:00:00',
               '2018-01-01 02:00:00'],
              dtype='datetime64[ns]', freq='H')
```

Manipulating and converting date times with timezone information

```
In [6]: dti = dti.tz_localize("UTC")

In [7]: dti
Out[7]:
DatetimeIndex(['2018-01-01 00:00:00+00:00', '2018-01-01 01:00:00+00:00',
               '2018-01-01 02:00:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='H')

In [8]: dti.tz_convert("US/Pacific")
Out[8]:
DatetimeIndex(['2017-12-31 16:00:00-08:00', '2017-12-31 17:00:00-08:00',
               '2017-12-31 18:00:00-08:00'],
              dtype='datetime64[ns, US/Pacific]', freq='H')
```

Resampling or converting a time series to a particular frequency

```
In [9]: idx = pd.date_range("2018-01-01", periods=5, freq="H")

In [10]: ts = pd.Series(range(len(idx)), index=idx)

In [11]: ts
Out[11]:
2018-01-01 00:00:00    0
```

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```
2018-01-01 01:00:00    1
2018-01-01 02:00:00    2
2018-01-01 03:00:00    3
2018-01-01 04:00:00    4
Freq: H, dtype: int64

In [12]: ts.resample("2H").mean()
Out[12]:
2018-01-01 00:00:00    0.5
2018-01-01 02:00:00    2.5
2018-01-01 04:00:00    4.0
Freq: 2H, dtype: float64
```

Performing date and time arithmetic with absolute or relative time increments

```
In [13]: friday = pd.Timestamp("2018-01-05")

In [14]: friday.day_name()
Out[14]: 'Friday'

# Add 1 day
In [15]: saturday = friday + pd.Timedelta("1 day")

In [16]: saturday.day_name()
Out[16]: 'Saturday'

# Add 1 business day (Friday --> Monday)
In [17]: monday = friday + pd.offsets.BDay()

In [18]: monday.day_name()
Out[18]: 'Monday'
```

pandas provides a relatively compact and self-contained set of tools for performing the above tasks and more.

2.19.1 Overview

pandas captures 4 general time related concepts:

1. Date times: A specific date and time with timezone support. Similar to `datetime.datetime` from the standard library.
2. Time deltas: An absolute time duration. Similar to `datetime.timedelta` from the standard library.
3. Time spans: A span of time defined by a point in time and its associated frequency.
4. Date offsets: A relative time duration that respects calendar arithmetic. Similar to `dateutil.relativedelta.relativedelta` from the `dateutil` package.

Concept	Scalar Class	Array Class	pandas Data Type	Primary Creation Method
Date times	`Timestamp`	`DatetimeIndex`	`datetime64[ns]` or `datetime64[ns, tz]`	`to_datetime` or `date_range`
Time deltas	`Timedelta`	`TimedeltaIndex`	`timedelta64[ns]`	`to_timedelta` or `timedelta_range`
Time spans	`Period`	`PeriodIndex`	`period[freq]`	`Period` or `period_range`
Date offsets	`DateOffset`	None	None	`DateOffset`

For time series data, it's conventional to represent the time component in the index of a *Series* or *DataFrame* so manipulations can be performed with respect to the time element.

```
In [19]: pd.Series(range(3), index=pd.date_range("2000", freq="D", periods=3))
Out[19]:
2000-01-01    0
2000-01-02    1
2000-01-03    2
Freq: D, dtype: int64
```

However, *Series* and *DataFrame* can directly also support the time component as data itself.

```
In [20]: pd.Series(pd.date_range("2000", freq="D", periods=3))
Out[20]:
0   2000-01-01
1   2000-01-02
2   2000-01-03
dtype: datetime64[ns]
```

Series and *DataFrame* have extended data type support and functionality for `datetime`, `timedelta` and `Period` data when passed into those constructors. `DateOffset` data however will be stored as `object` data.

```
In [21]: pd.Series(pd.period_range("1/1/2011", freq="M", periods=3))
Out[21]:
0    2011-01
1    2011-02
2    2011-03
dtype: period[M]

In [22]: pd.Series([pd.DateOffset(1), pd.DateOffset(2)])
Out[22]:
0         <DateOffset>
1    <2 * DateOffsets>
dtype: object

In [23]: pd.Series(pd.date_range("1/1/2011", freq="M", periods=3))
Out[23]:
0   2011-01-31
1   2011-02-28
2   2011-03-31
dtype: datetime64[ns]
```

Lastly, pandas represents null date times, time deltas, and time spans as `NaT` which is useful for representing missing or null date like values and behaves similar as `np.nan` does for float data.

```
In [24]: pd.Timestamp(pd.NaT)
Out[24]: NaT

In [25]: pd.Timedelta(pd.NaT)
Out[25]: NaT

In [26]: pd.Period(pd.NaT)
Out[26]: NaT

# Equality acts as np.nan would
In [27]: pd.NaT == pd.NaT
Out[27]: False
```

2.19.2 Timestamps vs. time spans

Timestamped data is the most basic type of time series data that associates values with points in time. For pandas objects it means using the points in time.

```
In [28]: pd.Timestamp(datetime.datetime(2012, 5, 1))
Out[28]: Timestamp('2012-05-01 00:00:00')

In [29]: pd.Timestamp("2012-05-01")
Out[29]: Timestamp('2012-05-01 00:00:00')

In [30]: pd.Timestamp(2012, 5, 1)
Out[30]: Timestamp('2012-05-01 00:00:00')
```

However, in many cases it is more natural to associate things like change variables with a time span instead. The span represented by `Period` can be specified explicitly, or inferred from datetime string format.

For example:

```
In [31]: pd.Period("2011-01")
Out[31]: Period('2011-01', 'M')

In [32]: pd.Period("2012-05", freq="D")
Out[32]: Period('2012-05-01', 'D')
```

`Timestamp` and *`Period`* can serve as an index. Lists of `Timestamp` and `Period` are automatically coerced to *`DatetimeIndex`* and *`PeriodIndex`* respectively.

```
In [33]: dates = [
   ....:     pd.Timestamp("2012-05-01"),
   ....:     pd.Timestamp("2012-05-02"),
   ....:     pd.Timestamp("2012-05-03"),
   ....: ]
   ....:

In [34]: ts = pd.Series(np.random.randn(3), dates)

In [35]: type(ts.index)
Out[35]: pandas.core.indexes.datetimes.DatetimeIndex

In [36]: ts.index
Out[36]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype=
↪'datetime64[ns]', freq=None)
```

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```
In [37]: ts
Out[37]:
2012-05-01    0.469112
2012-05-02   -0.282863
2012-05-03   -1.509059
dtype: float64

In [38]: periods = [pd.Period("2012-01"), pd.Period("2012-02"), pd.Period("2012-03")]

In [39]: ts = pd.Series(np.random.randn(3), periods)

In [40]: type(ts.index)
Out[40]: pandas.core.indexes.period.PeriodIndex

In [41]: ts.index
Out[41]: PeriodIndex(['2012-01', '2012-02', '2012-03'], dtype='period[M]', freq='M')

In [42]: ts
Out[42]:
2012-01   -1.135632
2012-02    1.212112
2012-03   -0.173215
Freq: M, dtype: float64
```

pandas allows you to capture both representations and convert between them. Under the hood, pandas represents timestamps using instances of `Timestamp` and sequences of timestamps using instances of `DatetimeIndex`. For regular time spans, pandas uses `Period` objects for scalar values and `PeriodIndex` for sequences of spans. Better support for irregular intervals with arbitrary start and end points are forth-coming in future releases.

2.19.3 Converting to timestamps

To convert a *Series* or list-like object of date-like objects e.g. strings, epochs, or a mixture, you can use the `to_datetime` function. When passed a `Series`, this returns a `Series` (with the same index), while a list-like is converted to a `DatetimeIndex`:

```
In [43]: pd.to_datetime(pd.Series(["Jul 31, 2009", "2010-01-10", None]))
Out[43]:
0   2009-07-31
1   2010-01-10
2          NaT
dtype: datetime64[ns]

In [44]: pd.to_datetime(["2005/11/23", "2010.12.31"])
Out[44]: DatetimeIndex(['2005-11-23', '2010-12-31'], dtype='datetime64[ns]',␣
↪freq=None)
```

If you use dates which start with the day first (i.e. European style), you can pass the `dayfirst` flag:

```
In [45]: pd.to_datetime(["04-01-2012 10:00"], dayfirst=True)
Out[45]: DatetimeIndex(['2012-01-04 10:00:00'], dtype='datetime64[ns]', freq=None)

In [46]: pd.to_datetime(["14-01-2012", "01-14-2012"], dayfirst=True)
Out[46]: DatetimeIndex(['2012-01-14', '2012-01-14'], dtype='datetime64[ns]',␣
↪freq=None)
```

Warning: You see in the above example that `dayfirst` isn't strict, so if a date can't be parsed with the day being first it will be parsed as if `dayfirst` were False.

If you pass a single string to `to_datetime`, it returns a single `Timestamp`. `Timestamp` can also accept string input, but it doesn't accept string parsing options like `dayfirst` or `format`, so use `to_datetime` if these are required.

```
In [47]: pd.to_datetime("2010/11/12")
Out[47]: Timestamp('2010-11-12 00:00:00')

In [48]: pd.Timestamp("2010/11/12")
Out[48]: Timestamp('2010-11-12 00:00:00')
```

You can also use the `DatetimeIndex` constructor directly:

```
In [49]: pd.DatetimeIndex(["2018-01-01", "2018-01-03", "2018-01-05"])
Out[49]: DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], dtype=
↪'datetime64[ns]', freq=None)
```

The string 'infer' can be passed in order to set the frequency of the index as the inferred frequency upon creation:

```
In [50]: pd.DatetimeIndex(["2018-01-01", "2018-01-03", "2018-01-05"], freq="infer")
Out[50]: DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], dtype=
↪'datetime64[ns]', freq='2D')
```

Providing a format argument

In addition to the required datetime string, a `format` argument can be passed to ensure specific parsing. This could also potentially speed up the conversion considerably.

```
In [51]: pd.to_datetime("2010/11/12", format="%Y/%m/%d")
Out[51]: Timestamp('2010-11-12 00:00:00')

In [52]: pd.to_datetime("12-11-2010 00:00", format="%d-%m-%Y %H:%M")
Out[52]: Timestamp('2010-11-12 00:00:00')
```

For more information on the choices available when specifying the `format` option, see the Python datetime documentation.

Assembling datetime from multiple DataFrame columns

You can also pass a `DataFrame` of integer or string columns to assemble into a `Series` of `Timestamps`.

```
In [53]: df = pd.DataFrame(
   ....:     {"year": [2015, 2016], "month": [2, 3], "day": [4, 5], "hour": [2, 3]}
   ....: )
   ....:

In [54]: pd.to_datetime(df)
Out[54]:
0   2015-02-04 02:00:00
1   2016-03-05 03:00:00
dtype: datetime64[ns]
```

You can pass only the columns that you need to assemble.

```
In [55]: pd.to_datetime(df[["year", "month", "day"]])
Out[55]:
0   2015-02-04
1   2016-03-05
dtype: datetime64[ns]
```

`pd.to_datetime` looks for standard designations of the datetime component in the column names, including:

- required: `year`, `month`, `day`
- optional: `hour`, `minute`, `second`, `millisecond`, `microsecond`, `nanosecond`

Invalid data

The default behavior, `errors='raise'`, is to raise when unparsable:

```
In [2]: pd.to_datetime(['2009/07/31', 'asd'], errors='raise')
ValueError: Unknown string format
```

Pass `errors='ignore'` to return the original input when unparsable:

```
In [56]: pd.to_datetime(["2009/07/31", "asd"], errors="ignore")
Out[56]: Index(['2009/07/31', 'asd'], dtype='object')
```

Pass `errors='coerce'` to convert unparsable data to `NaT` (not a time):

```
In [57]: pd.to_datetime(["2009/07/31", "asd"], errors="coerce")
Out[57]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)
```

Epoch timestamps

pandas supports converting integer or float epoch times to `Timestamp` and `DatetimeIndex`. The default unit is nanoseconds, since that is how `Timestamp` objects are stored internally. However, epochs are often stored in another `unit` which can be specified. These are computed from the starting point specified by the `origin` parameter.

```
In [58]: pd.to_datetime(
   ....:     [1349720105, 1349806505, 1349892905, 1349979305, 1350065705], unit="s"
   ....: )
   ....:
Out[58]:
DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05',
               '2012-10-10 18:15:05', '2012-10-11 18:15:05',
               '2012-10-12 18:15:05'],
              dtype='datetime64[ns]', freq=None)

In [59]: pd.to_datetime(
   ....:     [1349720105100, 1349720105200, 1349720105300, 1349720105400,␣
↪1349720105500],
   ....:     unit="ms",
   ....: )
   ....:
Out[59]:
DatetimeIndex(['2012-10-08 18:15:05.100000', '2012-10-08 18:15:05.200000',
               '2012-10-08 18:15:05.300000', '2012-10-08 18:15:05.400000',
```

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```
               '2012-10-08 18:15:05.500000'],
              dtype='datetime64[ns]', freq=None)
```

Note: The `unit` parameter does not use the same strings as the `format` parameter that was discussed *above*). The available units are listed on the documentation for *pandas.to_datetime()*.

Changed in version 1.0.0.

Constructing a *Timestamp* or *DatetimeIndex* with an epoch timestamp with the `tz` argument specified will raise a ValueError. If you have epochs in wall time in another timezone, you can read the epochs as timezone-naive timestamps and then localize to the appropriate timezone:

```
In [60]: pd.Timestamp(1262347200000000000).tz_localize("US/Pacific")
Out[60]: Timestamp('2010-01-01 12:00:00-0800', tz='US/Pacific')

In [61]: pd.DatetimeIndex([1262347200000000000]).tz_localize("US/Pacific")
Out[61]: DatetimeIndex(['2010-01-01 12:00:00-08:00'], dtype='datetime64[ns, US/
↪Pacific]', freq=None)
```

Note: Epoch times will be rounded to the nearest nanosecond.

Warning: Conversion of float epoch times can lead to inaccurate and unexpected results. Python floats have about 15 digits precision in decimal. Rounding during conversion from float to high precision `Timestamp` is unavoidable. The only way to achieve exact precision is to use a fixed-width types (e.g. an int64).

```
In [62]: pd.to_datetime([1490195805.433, 1490195805.433502912], unit="s")
Out[62]: DatetimeIndex(['2017-03-22 15:16:45.433000088', '2017-03-22 15:16:45.
↪433502913'], dtype='datetime64[ns]', freq=None)

In [63]: pd.to_datetime(1490195805433502912, unit="ns")
Out[63]: Timestamp('2017-03-22 15:16:45.433502912')
```

See also:

Using the origin Parameter

From timestamps to epoch

To invert the operation from above, namely, to convert from a `Timestamp` to a 'unix' epoch:

```
In [64]: stamps = pd.date_range("2012-10-08 18:15:05", periods=4, freq="D")

In [65]: stamps
Out[65]:
DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05',
               '2012-10-10 18:15:05', '2012-10-11 18:15:05'],
              dtype='datetime64[ns]', freq='D')
```

We subtract the epoch (midnight at January 1, 1970 UTC) and then floor divide by the "unit" (1 second).

```
In [66]: (stamps - pd.Timestamp("1970-01-01")) // pd.Timedelta("1s")
Out[66]: Int64Index([1349720105, 1349806505, 1349892905, 1349979305], dtype='int64')
```

Using the `origin` Parameter

Using the `origin` parameter, one can specify an alternative starting point for creation of a `DatetimeIndex`. For example, to use 1960-01-01 as the starting date:

```
In [67]: pd.to_datetime([1, 2, 3], unit="D", origin=pd.Timestamp("1960-01-01"))
Out[67]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to `1970-01-01 00:00:00`. Commonly called 'unix epoch' or POSIX time.

```
In [68]: pd.to_datetime([1, 2, 3], unit="D")
Out[68]: DatetimeIndex(['1970-01-02', '1970-01-03', '1970-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

2.19.4 Generating ranges of timestamps

To generate an index with timestamps, you can use either the `DatetimeIndex` or `Index` constructor and pass in a list of datetime objects:

```
In [69]: dates = [
   ....:     datetime.datetime(2012, 5, 1),
   ....:     datetime.datetime(2012, 5, 2),
   ....:     datetime.datetime(2012, 5, 3),
   ....: ]
   ....:

# Note the frequency information
In [70]: index = pd.DatetimeIndex(dates)

In [71]: index
Out[71]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype=
↪'datetime64[ns]', freq=None)

# Automatically converted to DatetimeIndex
In [72]: index = pd.Index(dates)

In [73]: index
Out[73]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype=
↪'datetime64[ns]', freq=None)
```

In practice this becomes very cumbersome because we often need a very long index with a large number of timestamps. If we need timestamps on a regular frequency, we can use the *`date_range()`* and *`bdate_range()`* functions to create a `DatetimeIndex`. The default frequency for `date_range` is a **calendar day** while the default for `bdate_range` is a **business day**:

```
In [74]: start = datetime.datetime(2011, 1, 1)

In [75]: end = datetime.datetime(2012, 1, 1)
```

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```
In [76]: index = pd.date_range(start, end)

In [77]: index
Out[77]:
DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03', '2011-01-04',
               '2011-01-05', '2011-01-06', '2011-01-07', '2011-01-08',
               '2011-01-09', '2011-01-10',
               ...
               '2011-12-23', '2011-12-24', '2011-12-25', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30',
               '2011-12-31', '2012-01-01'],
              dtype='datetime64[ns]', length=366, freq='D')

In [78]: index = pd.bdate_range(start, end)

In [79]: index
Out[79]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14',
               ...
               '2011-12-19', '2011-12-20', '2011-12-21', '2011-12-22',
               '2011-12-23', '2011-12-26', '2011-12-27', '2011-12-28',
               '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', length=260, freq='B')
```

Convenience functions like `date_range` and `bdate_range` can utilize a variety of *frequency aliases*:

```
In [80]: pd.date_range(start, periods=1000, freq="M")
Out[80]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-30',
               '2011-05-31', '2011-06-30', '2011-07-31', '2011-08-31',
               '2011-09-30', '2011-10-31',
               ...
               '2093-07-31', '2093-08-31', '2093-09-30', '2093-10-31',
               '2093-11-30', '2093-12-31', '2094-01-31', '2094-02-28',
               '2094-03-31', '2094-04-30'],
              dtype='datetime64[ns]', length=1000, freq='M')

In [81]: pd.bdate_range(start, periods=250, freq="BQS")
Out[81]:
DatetimeIndex(['2011-01-03', '2011-04-01', '2011-07-01', '2011-10-03',
               '2012-01-02', '2012-04-02', '2012-07-02', '2012-10-01',
               '2013-01-01', '2013-04-01',
               ...
               '2071-01-01', '2071-04-01', '2071-07-01', '2071-10-01',
               '2072-01-01', '2072-04-01', '2072-07-01', '2072-10-03',
               '2073-01-02', '2073-04-03'],
              dtype='datetime64[ns]', length=250, freq='BQS-JAN')
```

`date_range` and `bdate_range` make it easy to generate a range of dates using various combinations of parameters like `start`, `end`, `periods`, and `freq`. The start and end dates are strictly inclusive, so dates outside of those specified will not be generated:

```
In [82]: pd.date_range(start, end, freq="BM")
```

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```
Out[82]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
               '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
              dtype='datetime64[ns]', freq='BM')

In [83]: pd.date_range(start, end, freq="W")
Out[83]:
DatetimeIndex(['2011-01-02', '2011-01-09', '2011-01-16', '2011-01-23',
               '2011-01-30', '2011-02-06', '2011-02-13', '2011-02-20',
               '2011-02-27', '2011-03-06', '2011-03-13', '2011-03-20',
               '2011-03-27', '2011-04-03', '2011-04-10', '2011-04-17',
               '2011-04-24', '2011-05-01', '2011-05-08', '2011-05-15',
               '2011-05-22', '2011-05-29', '2011-06-05', '2011-06-12',
               '2011-06-19', '2011-06-26', '2011-07-03', '2011-07-10',
               '2011-07-17', '2011-07-24', '2011-07-31', '2011-08-07',
               '2011-08-14', '2011-08-21', '2011-08-28', '2011-09-04',
               '2011-09-11', '2011-09-18', '2011-09-25', '2011-10-02',
               '2011-10-09', '2011-10-16', '2011-10-23', '2011-10-30',
               '2011-11-06', '2011-11-13', '2011-11-20', '2011-11-27',
               '2011-12-04', '2011-12-11', '2011-12-18', '2011-12-25',
               '2012-01-01'],
              dtype='datetime64[ns]', freq='W-SUN')

In [84]: pd.bdate_range(end=end, periods=20)
Out[84]:
DatetimeIndex(['2011-12-05', '2011-12-06', '2011-12-07', '2011-12-08',
               '2011-12-09', '2011-12-12', '2011-12-13', '2011-12-14',
               '2011-12-15', '2011-12-16', '2011-12-19', '2011-12-20',
               '2011-12-21', '2011-12-22', '2011-12-23', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', freq='B')

In [85]: pd.bdate_range(start=start, periods=20)
Out[85]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14', '2011-01-17', '2011-01-18',
               '2011-01-19', '2011-01-20', '2011-01-21', '2011-01-24',
               '2011-01-25', '2011-01-26', '2011-01-27', '2011-01-28'],
              dtype='datetime64[ns]', freq='B')
```

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced dates from `start` to `end` inclusively, with `periods` number of elements in the resulting `DatetimeIndex`:

```
In [86]: pd.date_range("2018-01-01", "2018-01-05", periods=5)
Out[86]:
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05'],
              dtype='datetime64[ns]', freq=None)

In [87]: pd.date_range("2018-01-01", "2018-01-05", periods=10)
Out[87]:
DatetimeIndex(['2018-01-01 00:00:00', '2018-01-01 10:40:00',
               '2018-01-01 21:20:00', '2018-01-02 08:00:00',
               '2018-01-02 18:40:00', '2018-01-03 05:20:00',
```

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```
               '2018-01-03 16:00:00', '2018-01-04 02:40:00',
               '2018-01-04 13:20:00', '2018-01-05 00:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Custom frequency ranges

`bdate_range` can also generate a range of custom frequency dates by using the `weekmask` and `holidays` parameters. These parameters will only be used if a custom frequency string is passed.

```
In [88]: weekmask = "Mon Wed Fri"

In [89]: holidays = [datetime.datetime(2011, 1, 5), datetime.datetime(2011, 3, 14)]

In [90]: pd.bdate_range(start, end, freq="C", weekmask=weekmask, holidays=holidays)
Out[90]:
DatetimeIndex(['2011-01-03', '2011-01-07', '2011-01-10', '2011-01-12',
               '2011-01-14', '2011-01-17', '2011-01-19', '2011-01-21',
               '2011-01-24', '2011-01-26',
               ...
               '2011-12-09', '2011-12-12', '2011-12-14', '2011-12-16',
               '2011-12-19', '2011-12-21', '2011-12-23', '2011-12-26',
               '2011-12-28', '2011-12-30'],
              dtype='datetime64[ns]', length=154, freq='C')

In [91]: pd.bdate_range(start, end, freq="CBMS", weekmask=weekmask)
Out[91]:
DatetimeIndex(['2011-01-03', '2011-02-02', '2011-03-02', '2011-04-01',
               '2011-05-02', '2011-06-01', '2011-07-01', '2011-08-01',
               '2011-09-02', '2011-10-03', '2011-11-02', '2011-12-02'],
              dtype='datetime64[ns]', freq='CBMS')
```

See also:

Custom business days

2.19.5 Timestamp limitations

Since pandas represents timestamps in nanosecond resolution, the time span that can be represented using a 64-bit integer is limited to approximately 584 years:

```
In [92]: pd.Timestamp.min
Out[92]: Timestamp('1677-09-21 00:12:43.145225')

In [93]: pd.Timestamp.max
Out[93]: Timestamp('2262-04-11 23:47:16.854775807')
```

See also:

Representing out-of-bounds spans

2.19.6 Indexing

One of the main uses for `DatetimeIndex` is as an index for pandas objects. The `DatetimeIndex` class contains many time series related optimizations:

- A large range of dates for various offsets are pre-computed and cached under the hood in order to make generating subsequent date ranges very fast (just have to grab a slice).
- Fast shifting using the `shift` method on pandas objects.
- Unioning of overlapping `DatetimeIndex` objects with the same frequency is very fast (important for fast data alignment).
- Quick access to date fields via properties such as `year`, `month`, etc.
- Regularization functions like `snap` and very fast `asof` logic.

`DatetimeIndex` objects have all the basic functionality of regular `Index` objects, and a smorgasbord of advanced time series specific methods for easy frequency processing.

See also:

Reindexing methods

Note: While pandas does not force you to have a sorted date index, some of these methods may have unexpected or incorrect behavior if the dates are unsorted.

`DatetimeIndex` can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

```
In [94]: rng = pd.date_range(start, end, freq="BM")

In [95]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [96]: ts.index
Out[96]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
               '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
              dtype='datetime64[ns]', freq='BM')

In [97]: ts[:5].index
Out[97]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31'],
              dtype='datetime64[ns]', freq='BM')

In [98]: ts[::2].index
Out[98]:
DatetimeIndex(['2011-01-31', '2011-03-31', '2011-05-31', '2011-07-29',
               '2011-09-30', '2011-11-30'],
              dtype='datetime64[ns]', freq='2BM')
```

Partial string indexing

Dates and strings that parse to timestamps can be passed as indexing parameters:

```
In [99]: ts["1/31/2011"]
Out[99]: 0.11920871129693428

In [100]: ts[datetime.datetime(2011, 12, 25):]
Out[100]:
2011-12-30    0.56702
Freq: BM, dtype: float64

In [101]: ts["10/31/2011":"12/31/2011"]
Out[101]:
2011-10-31    0.271860
2011-11-30   -0.424972
2011-12-30    0.567020
Freq: BM, dtype: float64
```

To provide convenience for accessing longer time series, you can also pass in the year or year and month as strings:

```
In [102]: ts["2011"]
Out[102]:
2011-01-31    0.119209
2011-02-28   -1.044236
2011-03-31   -0.861849
2011-04-29   -2.104569
2011-05-31   -0.494929
2011-06-30    1.071804
2011-07-29    0.721555
2011-08-31   -0.706771
2011-09-30   -1.039575
2011-10-31    0.271860
2011-11-30   -0.424972
2011-12-30    0.567020
Freq: BM, dtype: float64

In [103]: ts["2011-6"]
Out[103]:
2011-06-30    1.071804
Freq: BM, dtype: float64
```

This type of slicing will work on a `DataFrame` with a `DatetimeIndex` as well. Since the partial string selection is a form of label slicing, the endpoints **will be** included. This would include matching times on an included date:

Warning: Indexing `DataFrame` rows with a *single* string with getitem (e.g. `frame[dtstring]`) is deprecated starting with pandas 1.2.0 (given the ambiguity whether it is indexing the rows or selecting a column) and will be removed in a future version. The equivalent with `.loc` (e.g. `frame.loc[dtstring]`) is still supported.

```
In [104]: dft = pd.DataFrame(
   .....:     np.random.randn(100000, 1),
   .....:     columns=["A"],
   .....:     index=pd.date_range("20130101", periods=100000, freq="T"),
   .....: )
   .....:
```

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```
In [105]: dft
Out[105]:
                            A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...                       ...
2013-03-11 10:35:00 -0.747967
2013-03-11 10:36:00 -0.034523
2013-03-11 10:37:00 -0.201754
2013-03-11 10:38:00 -1.509067
2013-03-11 10:39:00 -1.693043

[100000 rows x 1 columns]

In [106]: dft.loc["2013"]
Out[106]:
                            A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...                       ...
2013-03-11 10:35:00 -0.747967
2013-03-11 10:36:00 -0.034523
2013-03-11 10:37:00 -0.201754
2013-03-11 10:38:00 -1.509067
2013-03-11 10:39:00 -1.693043

[100000 rows x 1 columns]
```

This starts on the very first time in the month, and includes the last date and time for the month:

```
In [107]: dft["2013-1":"2013-2"]
Out[107]:
                            A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...                       ...
2013-02-28 23:55:00  0.850929
2013-02-28 23:56:00  0.976712
2013-02-28 23:57:00 -2.693884
2013-02-28 23:58:00 -1.575535
2013-02-28 23:59:00 -1.573517

[84960 rows x 1 columns]
```

This specifies a stop time **that includes all of the times on the last day**:

```
In [108]: dft["2013-1":"2013-2-28"]
Out[108]:
                            A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...                       ...
2013-02-28 23:55:00  0.850929
2013-02-28 23:56:00  0.976712
2013-02-28 23:57:00 -2.693884
2013-02-28 23:58:00 -1.575535
2013-02-28 23:59:00 -1.573517

[84960 rows x 1 columns]
```

This specifies an **exact** stop time (and is not the same as the above):

```
In [109]: dft["2013-1":"2013-2-28 00:00:00"]
Out[109]:
                            A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...                       ...
2013-02-27 23:56:00  1.197749
2013-02-27 23:57:00  0.720521
2013-02-27 23:58:00 -0.072718
2013-02-27 23:59:00 -0.681192
2013-02-28 00:00:00 -0.557501

[83521 rows x 1 columns]
```

We are stopping on the included end-point as it is part of the index:

```
In [110]: dft["2013-1-15":"2013-1-15 12:30:00"]
Out[110]:
                            A
2013-01-15 00:00:00 -0.984810
2013-01-15 00:01:00  0.941451
2013-01-15 00:02:00  1.559365
2013-01-15 00:03:00  1.034374
2013-01-15 00:04:00 -1.480656
...                       ...
2013-01-15 12:26:00  0.371454
2013-01-15 12:27:00 -0.930806
2013-01-15 12:28:00 -0.069177
2013-01-15 12:29:00  0.066510
2013-01-15 12:30:00 -0.003945

[751 rows x 1 columns]
```

`DatetimeIndex` partial string indexing also works on a `DataFrame` with a `MultiIndex`:

```
In [111]: dft2 = pd.DataFrame(
   .....:     np.random.randn(20, 1),
   .....:     columns=["A"],
   .....:     index=pd.MultiIndex.from_product(
   .....:         [pd.date_range("20130101", periods=10, freq="12H"), ["a", "b"]]
   .....:     ),
   .....: )
   .....:

In [112]: dft2
Out[112]:
                              A
2013-01-01 00:00:00 a -0.298694
                    b  0.823553
2013-01-01 12:00:00 a  0.943285
                    b -1.479399
2013-01-02 00:00:00 a -1.643342
...                         ...
2013-01-04 12:00:00 b  0.069036
2013-01-05 00:00:00 a  0.122297
                    b  1.422060
2013-01-05 12:00:00 a  0.370079
                    b  1.016331

[20 rows x 1 columns]

In [113]: dft2.loc["2013-01-05"]
Out[113]:
                              A
2013-01-05 00:00:00 a  0.122297
                    b  1.422060
2013-01-05 12:00:00 a  0.370079
                    b  1.016331

In [114]: idx = pd.IndexSlice

In [115]: dft2 = dft2.swaplevel(0, 1).sort_index()

In [116]: dft2.loc[idx[:, "2013-01-05"], :]
Out[116]:
                              A
a 2013-01-05 00:00:00  0.122297
  2013-01-05 12:00:00  0.370079
b 2013-01-05 00:00:00  1.422060
  2013-01-05 12:00:00  1.016331
```

New in version 0.25.0.

Slicing with string indexing also honors UTC offset.

```
In [117]: df = pd.DataFrame([0], index=pd.DatetimeIndex(["2019-01-01"], tz="US/Pacific
↪"))

In [118]: df
Out[118]:
                           0
2019-01-01 00:00:00-08:00  0
```

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```
In [119]: df["2019-01-01 12:00:00+04:00":"2019-01-01 13:00:00+04:00"]
Out[119]:
                            0
2019-01-01 00:00:00-08:00   0
```

Slice vs. exact match

The same string used as an indexing parameter can be treated either as a slice or as an exact match depending on the resolution of the index. If the string is less accurate than the index, it will be treated as a slice, otherwise as an exact match.

Consider a `Series` object with a minute resolution index:

```
In [120]: series_minute = pd.Series(
   .....:     [1, 2, 3],
   .....:     pd.DatetimeIndex(
   .....:         ["2011-12-31 23:59:00", "2012-01-01 00:00:00", "2012-01-01 00:02:00
↪"]
   .....:     ),
   .....: )
   .....:

In [121]: series_minute.index.resolution
Out[121]: 'minute'
```

A timestamp string less accurate than a minute gives a `Series` object.

```
In [122]: series_minute["2011-12-31 23"]
Out[122]:
2011-12-31 23:59:00    1
dtype: int64
```

A timestamp string with minute resolution (or more accurate), gives a scalar instead, i.e. it is not casted to a slice.

```
In [123]: series_minute["2011-12-31 23:59"]
Out[123]: 1

In [124]: series_minute["2011-12-31 23:59:00"]
Out[124]: 1
```

If index resolution is second, then the minute-accurate timestamp gives a `Series`.

```
In [125]: series_second = pd.Series(
   .....:     [1, 2, 3],
   .....:     pd.DatetimeIndex(
   .....:         ["2011-12-31 23:59:59", "2012-01-01 00:00:00", "2012-01-01 00:00:01
↪"]
   .....:     ),
   .....: )
   .....:

In [126]: series_second.index.resolution
Out[126]: 'second'

In [127]: series_second["2011-12-31 23:59"]
```

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```
Out[127]:
2011-12-31 23:59:59    1
dtype: int64
```

If the timestamp string is treated as a slice, it can be used to index `DataFrame` with `.loc[]` as well.

```
In [128]: dft_minute = pd.DataFrame(
   .....:     {"a": [1, 2, 3], "b": [4, 5, 6]}, index=series_minute.index
   .....: )
   .....:

In [129]: dft_minute.loc["2011-12-31 23"]
Out[129]:
                     a  b
2011-12-31 23:59:00  1  4
```

Warning: However, if the string is treated as an exact match, the selection in `DataFrame`'s `[]` will be column-wise and not row-wise, see *Indexing Basics*. For example `dft_minute['2011-12-31 23:59']` will raise `KeyError` as `'2012-12-31 23:59'` has the same resolution as the index and there is no column with such name:

To *always* have unambiguous selection, whether the row is treated as a slice or a single selection, use `.loc`.

```
In [130]: dft_minute.loc["2011-12-31 23:59"]
Out[130]:
a    1
b    4
Name: 2011-12-31 23:59:00, dtype: int64
```

Note also that `DatetimeIndex` resolution cannot be less precise than day.

```
In [131]: series_monthly = pd.Series(
   .....:     [1, 2, 3], pd.DatetimeIndex(["2011-12", "2012-01", "2012-02"])
   .....: )
   .....:

In [132]: series_monthly.index.resolution
Out[132]: 'day'

In [133]: series_monthly["2011-12"]  # returns Series
Out[133]:
2011-12-01    1
dtype: int64
```

Exact indexing

As discussed in previous section, indexing a `DatetimeIndex` with a partial string depends on the "accuracy" of the period, in other words how specific the interval is in relation to the resolution of the index. In contrast, indexing with `Timestamp` or `datetime` objects is exact, because the objects have exact meaning. These also follow the semantics of *including both endpoints*.

These `Timestamp` and `datetime` objects have exact `hours, minutes,` and `seconds`, even though they were not explicitly specified (they are `0`).

```
In [134]: dft[datetime.datetime(2013, 1, 1): datetime.datetime(2013, 2, 28)]
Out[134]:
                            A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...                       ...
2013-02-27 23:56:00  1.197749
2013-02-27 23:57:00  0.720521
2013-02-27 23:58:00 -0.072718
2013-02-27 23:59:00 -0.681192
2013-02-28 00:00:00 -0.557501

[83521 rows x 1 columns]
```

With no defaults.

```
In [135]: dft[
   .....:     datetime.datetime(2013, 1, 1, 10, 12, 0): datetime.datetime(
   .....:         2013, 2, 28, 10, 12, 0
   .....:     )
   .....: ]
   .....:
Out[135]:
                            A
2013-01-01 10:12:00  0.565375
2013-01-01 10:13:00  0.068184
2013-01-01 10:14:00  0.788871
2013-01-01 10:15:00 -0.280343
2013-01-01 10:16:00  0.931536
...                       ...
2013-02-28 10:08:00  0.148098
2013-02-28 10:09:00 -0.388138
2013-02-28 10:10:00  0.139348
2013-02-28 10:11:00  0.085288
2013-02-28 10:12:00  0.950146

[83521 rows x 1 columns]
```

Truncating & fancy indexing

A *truncate()* convenience function is provided that is similar to slicing. Note that `truncate` assumes a 0 value for any unspecified date component in a `DatetimeIndex` in contrast to slicing which returns any partially matching dates:

```
In [136]: rng2 = pd.date_range("2011-01-01", "2012-01-01", freq="W")

In [137]: ts2 = pd.Series(np.random.randn(len(rng2)), index=rng2)

In [138]: ts2.truncate(before="2011-11", after="2011-12")
Out[138]:
2011-11-06    0.437823
2011-11-13   -0.293083
2011-11-20   -0.059881
2011-11-27    1.252450
Freq: W-SUN, dtype: float64

In [139]: ts2["2011-11":"2011-12"]
Out[139]:
2011-11-06    0.437823
2011-11-13   -0.293083
2011-11-20   -0.059881
2011-11-27    1.252450
2011-12-04    0.046611
2011-12-11    0.059478
2011-12-18   -0.286539
2011-12-25    0.841669
Freq: W-SUN, dtype: float64
```

Even complicated fancy indexing that breaks the `DatetimeIndex` frequency regularity will result in a `DatetimeIndex`, although frequency is lost:

```
In [140]: ts2[[0, 2, 6]].index
Out[140]: DatetimeIndex(['2011-01-02', '2011-01-16', '2011-02-13'], dtype=
↪'datetime64[ns]', freq=None)
```

2.19.7 Time/date components

There are several time/date properties that one can access from `Timestamp` or a collection of timestamps like a `DatetimeIndex`.

Property	Description
year	The year of the datetime
month	The month of the datetime
day	The days of the datetime
hour	The hour of the datetime
minute	The minutes of the datetime
second	The seconds of the datetime
microsecond	The microseconds of the datetime
nanosecond	The nanoseconds of the datetime
date	Returns datetime.date (does not contain timezone information)
time	Returns datetime.time (does not contain timezone information)
timetz	Returns datetime.time as local time with timezone information
dayofyear	The ordinal day of year
day_of_year	The ordinal day of year
weekofyear	The week ordinal of the year
week	The week ordinal of the year
dayofweek	The number of the day of the week with Monday=0, Sunday=6
day_of_week	The number of the day of the week with Monday=0, Sunday=6
weekday	The number of the day of the week with Monday=0, Sunday=6
quarter	Quarter of the date: Jan-Mar = 1, Apr-Jun = 2, etc.
days_in_month	The number of days in the month of the datetime
is_month_start	Logical indicating if first day of month (defined by frequency)
is_month_end	Logical indicating if last day of month (defined by frequency)
is_quarter_start	Logical indicating if first day of quarter (defined by frequency)
is_quarter_end	Logical indicating if last day of quarter (defined by frequency)
is_year_start	Logical indicating if first day of year (defined by frequency)
is_year_end	Logical indicating if last day of year (defined by frequency)
is_leap_year	Logical indicating if the date belongs to a leap year

Furthermore, if you have a `Series` with datetimelike values, then you can access these properties via the `.dt` accessor, as detailed in the section on *.dt accessors*.

New in version 1.1.0.

You may obtain the year, week and day components of the ISO year from the ISO 8601 standard:

```
In [141]: idx = pd.date_range(start="2019-12-29", freq="D", periods=4)

In [142]: idx.isocalendar()
Out[142]:
            year  week  day
2019-12-29  2019    52    7
2019-12-30  2020     1    1
2019-12-31  2020     1    2
2020-01-01  2020     1    3

In [143]: idx.to_series().dt.isocalendar()
Out[143]:
            year  week  day
2019-12-29  2019    52    7
2019-12-30  2020     1    1
2019-12-31  2020     1    2
2020-01-01  2020     1    3
```

2.19.8 DateOffset objects

In the preceding examples, frequency strings (e.g. `'D'`) were used to specify a frequency that defined:

- how the date times in *DatetimeIndex* were spaced when using *date_range()*
- the frequency of a *Period* or *PeriodIndex*

These frequency strings map to a `DateOffset` object and its subclasses. A `DateOffset` is similar to a *Timedelta* that represents a duration of time but follows specific calendar duration rules. For example, a *Timedelta* day will always increment `datetimes` by 24 hours, while a `DateOffset` day will increment `datetimes` to the same time the next day whether a day represents 23, 24 or 25 hours due to daylight savings time. However, all `DateOffset` subclasses that are an hour or smaller (`Hour`, `Minute`, `Second`, `Milli`, `Micro`, `Nano`) behave like *Timedelta* and respect absolute time.

The basic `DateOffset` acts similar to `dateutil.relativedelta` (relativedelta documentation) that shifts a date time by the corresponding calendar duration specified. The arithmetic operator (`+`) or the `apply` method can be used to perform the shift.

```
# This particular day contains a day light savings time transition
In [144]: ts = pd.Timestamp("2016-10-30 00:00:00", tz="Europe/Helsinki")

# Respects absolute time
In [145]: ts + pd.Timedelta(days=1)
Out[145]: Timestamp('2016-10-30 23:00:00+0200', tz='Europe/Helsinki')

# Respects calendar time
In [146]: ts + pd.DateOffset(days=1)
Out[146]: Timestamp('2016-10-31 00:00:00+0200', tz='Europe/Helsinki')

In [147]: friday = pd.Timestamp("2018-01-05")

In [148]: friday.day_name()
Out[148]: 'Friday'

# Add 2 business days (Friday --> Tuesday)
In [149]: two_business_days = 2 * pd.offsets.BDay()

In [150]: two_business_days.apply(friday)
Out[150]: Timestamp('2018-01-09 00:00:00')

In [151]: friday + two_business_days
Out[151]: Timestamp('2018-01-09 00:00:00')

In [152]: (friday + two_business_days).day_name()
Out[152]: 'Tuesday'
```

Most `DateOffsets` have associated frequencies strings, or offset aliases, that can be passed into `freq` keyword arguments. The available date offsets and associated frequency strings can be found below:

Date Offset	Frequency String	Description
DateOffset	None	Generic offset class, defaults to absolute 24 hours
BDay or *BusinessDay*	`'B'`	business day (weekday)
CDay or *CustomBusinessDay*	`'C'`	custom business day

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Table 3 – continued from previous page

Date Offset	Frequency String	Description
Week	'W'	one week, optionally anchored on a day of the week
WeekOfMonth	'WOM'	the x-th day of the y-th week of each month
LastWeekOfMonth	'LWOM'	the x-th day of the last week of each month
MonthEnd	'M'	calendar month end
MonthBegin	'MS'	calendar month begin
BMonthEnd or *BusinessMonthEnd*	'BM'	business month end
BMonthBegin or *BusinessMonthBegin*	'BMS'	business month begin
CBMonthEnd or *CustomBusinessMonthEnd*	'CBM'	custom business month end
CBMonthBegin or *CustomBusinessMonthBegin*	'CBMS'	custom business month begin
SemiMonthEnd	'SM'	15th (or other day_of_month) and calendar month end
SemiMonthBegin	'SMS'	15th (or other day_of_month) and calendar month begin
QuarterEnd	'Q'	calendar quarter end
QuarterBegin	'QS'	calendar quarter begin
BQuarterEnd	'BQ	business quarter end
BQuarterBegin	'BQS'	business quarter begin
FY5253Quarter	'REQ'	retail (aka 52-53 week) quarter
YearEnd	'A'	calendar year end
YearBegin	'AS' or 'BYS'	calendar year begin
BYearEnd	'BA'	business year end
BYearBegin	'BAS'	business year begin
FY5253	'RE'	retail (aka 52-53 week) year
Easter	None	Easter holiday
BusinessHour	'BH'	business hour
CustomBusinessHour	'CBH'	custom business hour
Day	'D'	one absolute day
Hour	'H'	one hour
Minute	'T' or 'min'	one minute
Second	'S'	one second
Milli	'L' or 'ms'	one millisecond
Micro	'U' or 'us'	one microsecond
Nano	'N'	one nanosecond

`DateOffsets` additionally have `rollforward()` and `rollback()` methods for moving a date forward or backward respectively to a valid offset date relative to the offset. For example, business offsets will roll dates that land on the weekends (Saturday and Sunday) forward to Monday since business offsets operate on the weekdays.

```
In [153]: ts = pd.Timestamp("2018-01-06 00:00:00")

In [154]: ts.day_name()
Out[154]: 'Saturday'
```

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```
# BusinessHour's valid offset dates are Monday through Friday
In [155]: offset = pd.offsets.BusinessHour(start="09:00")

# Bring the date to the closest offset date (Monday)
In [156]: offset.rollforward(ts)
Out[156]: Timestamp('2018-01-08 09:00:00')

# Date is brought to the closest offset date first and then the hour is added
In [157]: ts + offset
Out[157]: Timestamp('2018-01-08 10:00:00')
```

These operations preserve time (hour, minute, etc) information by default. To reset time to midnight, use `normalize()` before or after applying the operation (depending on whether you want the time information included in the operation).

```
In [158]: ts = pd.Timestamp("2014-01-01 09:00")

In [159]: day = pd.offsets.Day()

In [160]: day.apply(ts)
Out[160]: Timestamp('2014-01-02 09:00:00')

In [161]: day.apply(ts).normalize()
Out[161]: Timestamp('2014-01-02 00:00:00')

In [162]: ts = pd.Timestamp("2014-01-01 22:00")

In [163]: hour = pd.offsets.Hour()

In [164]: hour.apply(ts)
Out[164]: Timestamp('2014-01-01 23:00:00')

In [165]: hour.apply(ts).normalize()
Out[165]: Timestamp('2014-01-01 00:00:00')

In [166]: hour.apply(pd.Timestamp("2014-01-01 23:30")).normalize()
Out[166]: Timestamp('2014-01-02 00:00:00')
```

Parametric offsets

Some of the offsets can be "parameterized" when created to result in different behaviors. For example, the `Week` offset for generating weekly data accepts a `weekday` parameter which results in the generated dates always lying on a particular day of the week:

```
In [167]: d = datetime.datetime(2008, 8, 18, 9, 0)

In [168]: d
Out[168]: datetime.datetime(2008, 8, 18, 9, 0)

In [169]: d + pd.offsets.Week()
Out[169]: Timestamp('2008-08-25 09:00:00')

In [170]: d + pd.offsets.Week(weekday=4)
Out[170]: Timestamp('2008-08-22 09:00:00')
```

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```
In [171]: (d + pd.offsets.Week(weekday=4)).weekday()
Out[171]: 4

In [172]: d - pd.offsets.Week()
Out[172]: Timestamp('2008-08-11 09:00:00')
```

The `normalize` option will be effective for addition and subtraction.

```
In [173]: d + pd.offsets.Week(normalize=True)
Out[173]: Timestamp('2008-08-25 00:00:00')

In [174]: d - pd.offsets.Week(normalize=True)
Out[174]: Timestamp('2008-08-11 00:00:00')
```

Another example is parameterizing `YearEnd` with the specific ending month:

```
In [175]: d + pd.offsets.YearEnd()
Out[175]: Timestamp('2008-12-31 09:00:00')

In [176]: d + pd.offsets.YearEnd(month=6)
Out[176]: Timestamp('2009-06-30 09:00:00')
```

Using offsets with `Series` / `DatetimeIndex`

Offsets can be used with either a `Series` or `DatetimeIndex` to apply the offset to each element.

```
In [177]: rng = pd.date_range("2012-01-01", "2012-01-03")

In [178]: s = pd.Series(rng)

In [179]: rng
Out[179]: DatetimeIndex(['2012-01-01', '2012-01-02', '2012-01-03'], dtype=
↪'datetime64[ns]', freq='D')

In [180]: rng + pd.DateOffset(months=2)
Out[180]: DatetimeIndex(['2012-03-01', '2012-03-02', '2012-03-03'], dtype=
↪'datetime64[ns]', freq=None)

In [181]: s + pd.DateOffset(months=2)
Out[181]:
0   2012-03-01
1   2012-03-02
2   2012-03-03
dtype: datetime64[ns]

In [182]: s - pd.DateOffset(months=2)
Out[182]:
0   2011-11-01
1   2011-11-02
2   2011-11-03
dtype: datetime64[ns]
```

If the offset class maps directly to a `Timedelta` (`Day`, `Hour`, `Minute`, `Second`, `Micro`, `Milli`, `Nano`) it can be used exactly like a `Timedelta` - see the *Timedelta section* for more examples.

```
In [183]: s - pd.offsets.Day(2)
Out[183]:
0   2011-12-30
1   2011-12-31
2   2012-01-01
dtype: datetime64[ns]

In [184]: td = s - pd.Series(pd.date_range("2011-12-29", "2011-12-31"))

In [185]: td
Out[185]:
0   3 days
1   3 days
2   3 days
dtype: timedelta64[ns]

In [186]: td + pd.offsets.Minute(15)
Out[186]:
0   3 days 00:15:00
1   3 days 00:15:00
2   3 days 00:15:00
dtype: timedelta64[ns]
```

Note that some offsets (such as `BQuarterEnd`) do not have a vectorized implementation. They can still be used but may calculate significantly slower and will show a `PerformanceWarning`

```
In [187]: rng + pd.offsets.BQuarterEnd()
Out[187]: DatetimeIndex(['2012-03-30', '2012-03-30', '2012-03-30'], dtype=
↪'datetime64[ns]', freq=None)
```

Custom business days

The `CDay` or `CustomBusinessDay` class provides a parametric `BusinessDay` class which can be used to create customized business day calendars which account for local holidays and local weekend conventions.

As an interesting example, let's look at Egypt where a Friday-Saturday weekend is observed.

```
In [188]: weekmask_egypt = "Sun Mon Tue Wed Thu"

# They also observe International Workers' Day so let's
# add that for a couple of years
In [189]: holidays = [
   .....:     "2012-05-01",
   .....:     datetime.datetime(2013, 5, 1),
   .....:     np.datetime64("2014-05-01"),
   .....: ]
   .....:

In [190]: bday_egypt = pd.offsets.CustomBusinessDay(
   .....:     holidays=holidays,
   .....:     weekmask=weekmask_egypt,
   .....: )
   .....:

In [191]: dt = datetime.datetime(2013, 4, 30)
```

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```
In [192]: dt + 2 * bday_egypt
Out[192]: Timestamp('2013-05-05 00:00:00')
```

Let's map to the weekday names:

```
In [193]: dts = pd.date_range(dt, periods=5, freq=bday_egypt)

In [194]: pd.Series(dts.weekday, dts).map(pd.Series("Mon Tue Wed Thu Fri Sat Sun".
↪split()))
Out[194]:
2013-04-30    Tue
2013-05-02    Thu
2013-05-05    Sun
2013-05-06    Mon
2013-05-07    Tue
Freq: C, dtype: object
```

Holiday calendars can be used to provide the list of holidays. See the *holiday calendar* section for more information.

```
In [195]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [196]: bday_us = pd.offsets.CustomBusinessDay(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [197]: dt = datetime.datetime(2014, 1, 17)

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [198]: dt + bday_us
Out[198]: Timestamp('2014-01-21 00:00:00')
```

Monthly offsets that respect a certain holiday calendar can be defined in the usual way.

```
In [199]: bmth_us = pd.offsets.
↪CustomBusinessMonthBegin(calendar=USFederalHolidayCalendar())

# Skip new years
In [200]: dt = datetime.datetime(2013, 12, 17)

In [201]: dt + bmth_us
Out[201]: Timestamp('2014-01-02 00:00:00')

# Define date index with custom offset
In [202]: pd.date_range(start="20100101", end="20120101", freq=bmth_us)
Out[202]:
DatetimeIndex(['2010-01-04', '2010-02-01', '2010-03-01', '2010-04-01',
               '2010-05-03', '2010-06-01', '2010-07-01', '2010-08-02',
               '2010-09-01', '2010-10-01', '2010-11-01', '2010-12-01',
               '2011-01-03', '2011-02-01', '2011-03-01', '2011-04-01',
               '2011-05-02', '2011-06-01', '2011-07-01', '2011-08-01',
               '2011-09-01', '2011-10-03', '2011-11-01', '2011-12-01'],
              dtype='datetime64[ns]', freq='CBMS')
```

Note: The frequency string 'C' is used to indicate that a CustomBusinessDay DateOffset is used, it is important to note that since CustomBusinessDay is a parameterised type, instances of CustomBusinessDay may differ and this is not detectable from the 'C' frequency string. The user therefore needs to ensure that the 'C' frequency string is used

consistently within the user's application.

Business hour

The `BusinessHour` class provides a business hour representation on `BusinessDay`, allowing to use specific start and end times.

By default, `BusinessHour` uses 9:00 - 17:00 as business hours. Adding `BusinessHour` will increment `Timestamp` by hourly frequency. If target `Timestamp` is out of business hours, move to the next business hour then increment it. If the result exceeds the business hours end, the remaining hours are added to the next business day.

```
In [203]: bh = pd.offsets.BusinessHour()

In [204]: bh
Out[204]: <BusinessHour: BH=09:00-17:00>

# 2014-08-01 is Friday
In [205]: pd.Timestamp("2014-08-01 10:00").weekday()
Out[205]: 4

In [206]: pd.Timestamp("2014-08-01 10:00") + bh
Out[206]: Timestamp('2014-08-01 11:00:00')

# Below example is the same as: pd.Timestamp('2014-08-01 09:00') + bh
In [207]: pd.Timestamp("2014-08-01 08:00") + bh
Out[207]: Timestamp('2014-08-01 10:00:00')

# If the results is on the end time, move to the next business day
In [208]: pd.Timestamp("2014-08-01 16:00") + bh
Out[208]: Timestamp('2014-08-04 09:00:00')

# Remainings are added to the next day
In [209]: pd.Timestamp("2014-08-01 16:30") + bh
Out[209]: Timestamp('2014-08-04 09:30:00')

# Adding 2 business hours
In [210]: pd.Timestamp("2014-08-01 10:00") + pd.offsets.BusinessHour(2)
Out[210]: Timestamp('2014-08-01 12:00:00')

# Subtracting 3 business hours
In [211]: pd.Timestamp("2014-08-01 10:00") + pd.offsets.BusinessHour(-3)
Out[211]: Timestamp('2014-07-31 15:00:00')
```

You can also specify `start` and `end` time by keywords. The argument must be a `str` with an `hour:minute` representation or a `datetime.time` instance. Specifying seconds, microseconds and nanoseconds as business hour results in `ValueError`.

```
In [212]: bh = pd.offsets.BusinessHour(start="11:00", end=datetime.time(20, 0))

In [213]: bh
Out[213]: <BusinessHour: BH=11:00-20:00>

In [214]: pd.Timestamp("2014-08-01 13:00") + bh
Out[214]: Timestamp('2014-08-01 14:00:00')

In [215]: pd.Timestamp("2014-08-01 09:00") + bh
```

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```
Out[215]: Timestamp('2014-08-01 12:00:00')

In [216]: pd.Timestamp("2014-08-01 18:00") + bh
Out[216]: Timestamp('2014-08-01 19:00:00')
```

Passing `start` time later than `end` represents midnight business hour. In this case, business hour exceeds midnight and overlap to the next day. Valid business hours are distinguished by whether it started from valid `BusinessDay`.

```
In [217]: bh = pd.offsets.BusinessHour(start="17:00", end="09:00")

In [218]: bh
Out[218]: <BusinessHour: BH=17:00-09:00>

In [219]: pd.Timestamp("2014-08-01 17:00") + bh
Out[219]: Timestamp('2014-08-01 18:00:00')

In [220]: pd.Timestamp("2014-08-01 23:00") + bh
Out[220]: Timestamp('2014-08-02 00:00:00')

# Although 2014-08-02 is Saturday,
# it is valid because it starts from 08-01 (Friday).
In [221]: pd.Timestamp("2014-08-02 04:00") + bh
Out[221]: Timestamp('2014-08-02 05:00:00')

# Although 2014-08-04 is Monday,
# it is out of business hours because it starts from 08-03 (Sunday).
In [222]: pd.Timestamp("2014-08-04 04:00") + bh
Out[222]: Timestamp('2014-08-04 18:00:00')
```

Applying `BusinessHour.rollforward` and `rollback` to out of business hours results in the next business hour start or previous day's end. Different from other offsets, `BusinessHour.rollforward` may output different results from `apply` by definition.

This is because one day's business hour end is equal to next day's business hour start. For example, under the default business hours (9:00 - 17:00), there is no gap (0 minutes) between `2014-08-01 17:00` and `2014-08-04 09:00`.

```
# This adjusts a Timestamp to business hour edge
In [223]: pd.offsets.BusinessHour().rollback(pd.Timestamp("2014-08-02 15:00"))
Out[223]: Timestamp('2014-08-01 17:00:00')

In [224]: pd.offsets.BusinessHour().rollforward(pd.Timestamp("2014-08-02 15:00"))
Out[224]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessHour().apply(pd.Timestamp('2014-08-01 17:00')).
# And it is the same as BusinessHour().apply(pd.Timestamp('2014-08-04 09:00'))
In [225]: pd.offsets.BusinessHour().apply(pd.Timestamp("2014-08-02 15:00"))
Out[225]: Timestamp('2014-08-04 10:00:00')

# BusinessDay results (for reference)
In [226]: pd.offsets.BusinessHour().rollforward(pd.Timestamp("2014-08-02"))
Out[226]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessDay().apply(pd.Timestamp('2014-08-01'))
# The result is the same as rollworward because BusinessDay never overlap.
In [227]: pd.offsets.BusinessHour().apply(pd.Timestamp("2014-08-02"))
Out[227]: Timestamp('2014-08-04 10:00:00')
```

`BusinessHour` regards Saturday and Sunday as holidays. To use arbitrary holidays, you can use `CustomBusinessHour` offset, as explained in the following subsection.

Custom business hour

The `CustomBusinessHour` is a mixture of `BusinessHour` and `CustomBusinessDay` which allows you to specify arbitrary holidays. `CustomBusinessHour` works as the same as `BusinessHour` except that it skips specified custom holidays.

```
In [228]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [229]: bhour_us = pd.offsets.
↪CustomBusinessHour(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [230]: dt = datetime.datetime(2014, 1, 17, 15)

In [231]: dt + bhour_us
Out[231]: Timestamp('2014-01-17 16:00:00')

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [232]: dt + bhour_us * 2
Out[232]: Timestamp('2014-01-21 09:00:00')
```

You can use keyword arguments supported by either `BusinessHour` and `CustomBusinessDay`.

```
In [233]: bhour_mon = pd.offsets.CustomBusinessHour(start="10:00", weekmask="Tue Wed␣
↪Thu Fri")

# Monday is skipped because it's a holiday, business hour starts from 10:00
In [234]: dt + bhour_mon * 2
Out[234]: Timestamp('2014-01-21 10:00:00')
```

Offset aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as *offset aliases*.

Alias	Description
B	business day frequency
C	custom business day frequency
D	calendar day frequency
W	weekly frequency
M	month end frequency
SM	semi-month end frequency (15th and end of month)
BM	business month end frequency
CBM	custom business month end frequency
MS	month start frequency
SMS	semi-month start frequency (1st and 15th)
BMS	business month start frequency
CBMS	custom business month start frequency
Q	quarter end frequency
BQ	business quarter end frequency
QS	quarter start frequency
BQS	business quarter start frequency
A, Y	year end frequency
BA, BY	business year end frequency
AS, YS	year start frequency
BAS, BYS	business year start frequency
BH	business hour frequency
H	hourly frequency
T, min	minutely frequency
S	secondly frequency
L, ms	milliseconds
U, us	microseconds
N	nanoseconds

Combining aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

```
In [235]: pd.date_range(start, periods=5, freq="B")
Out[235]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07'],
              dtype='datetime64[ns]', freq='B')

In [236]: pd.date_range(start, periods=5, freq=pd.offsets.BDay())
Out[236]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07'],
              dtype='datetime64[ns]', freq='B')
```

You can combine together day and intraday offsets:

```
In [237]: pd.date_range(start, periods=10, freq="2h20min")
Out[237]:
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-01 02:20:00',
               '2011-01-01 04:40:00', '2011-01-01 07:00:00',
               '2011-01-01 09:20:00', '2011-01-01 11:40:00',
```

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```
               '2011-01-01 14:00:00', '2011-01-01 16:20:00',
               '2011-01-01 18:40:00', '2011-01-01 21:00:00'],
              dtype='datetime64[ns]', freq='140T')

In [238]: pd.date_range(start, periods=10, freq="1D10U")
Out[238]:
DatetimeIndex([       '2011-01-01 00:00:00', '2011-01-02 00:00:00.000010',
               '2011-01-03 00:00:00.000020', '2011-01-04 00:00:00.000030',
               '2011-01-05 00:00:00.000040', '2011-01-06 00:00:00.000050',
               '2011-01-07 00:00:00.000060', '2011-01-08 00:00:00.000070',
               '2011-01-09 00:00:00.000080', '2011-01-10 00:00:00.000090'],
              dtype='datetime64[ns]', freq='86400000010U')
```

Anchored offsets

For some frequencies you can specify an anchoring suffix:

Alias	Description
W-SUN	weekly frequency (Sundays). Same as 'W'
W-MON	weekly frequency (Mondays)
W-TUE	weekly frequency (Tuesdays)
W-WED	weekly frequency (Wednesdays)
W-THU	weekly frequency (Thursdays)
W-FRI	weekly frequency (Fridays)
W-SAT	weekly frequency (Saturdays)
(B)Q(S)-DEC	quarterly frequency, year ends in December. Same as 'Q'
(B)Q(S)-JAN	quarterly frequency, year ends in January
(B)Q(S)-FEB	quarterly frequency, year ends in February
(B)Q(S)-MAR	quarterly frequency, year ends in March
(B)Q(S)-APR	quarterly frequency, year ends in April
(B)Q(S)-MAY	quarterly frequency, year ends in May
(B)Q(S)-JUN	quarterly frequency, year ends in June
(B)Q(S)-JUL	quarterly frequency, year ends in July
(B)Q(S)-AUG	quarterly frequency, year ends in August
(B)Q(S)-SEP	quarterly frequency, year ends in September
(B)Q(S)-OCT	quarterly frequency, year ends in October
(B)Q(S)-NOV	quarterly frequency, year ends in November
(B)A(S)-DEC	annual frequency, anchored end of December. Same as 'A'

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Table 4 – continued from previous page

Alias	Description
(B)A(S)-JAN	annual frequency, anchored end of January
(B)A(S)-FEB	annual frequency, anchored end of February
(B)A(S)-MAR	annual frequency, anchored end of March
(B)A(S)-APR	annual frequency, anchored end of April
(B)A(S)-MAY	annual frequency, anchored end of May
(B)A(S)-JUN	annual frequency, anchored end of June
(B)A(S)-JUL	annual frequency, anchored end of July
(B)A(S)-AUG	annual frequency, anchored end of August
(B)A(S)-SEP	annual frequency, anchored end of September
(B)A(S)-OCT	annual frequency, anchored end of October
(B)A(S)-NOV	annual frequency, anchored end of November

These can be used as arguments to `date_range`, `bdate_range`, constructors for `DatetimeIndex`, as well as various other timeseries-related functions in pandas.

Anchored offset semantics

For those offsets that are anchored to the start or end of specific frequency (`MonthEnd`, `MonthBegin`, `WeekEnd`, etc), the following rules apply to rolling forward and backwards.

When `n` is not 0, if the given date is not on an anchor point, it snapped to the next(previous) anchor point, and moved `|n|-1` additional steps forwards or backwards.

```
In [239]: pd.Timestamp("2014-01-02") + pd.offsets.MonthBegin(n=1)
Out[239]: Timestamp('2014-02-01 00:00:00')

In [240]: pd.Timestamp("2014-01-02") + pd.offsets.MonthEnd(n=1)
Out[240]: Timestamp('2014-01-31 00:00:00')

In [241]: pd.Timestamp("2014-01-02") - pd.offsets.MonthBegin(n=1)
Out[241]: Timestamp('2014-01-01 00:00:00')

In [242]: pd.Timestamp("2014-01-02") - pd.offsets.MonthEnd(n=1)
Out[242]: Timestamp('2013-12-31 00:00:00')

In [243]: pd.Timestamp("2014-01-02") + pd.offsets.MonthBegin(n=4)
Out[243]: Timestamp('2014-05-01 00:00:00')

In [244]: pd.Timestamp("2014-01-02") - pd.offsets.MonthBegin(n=4)
Out[244]: Timestamp('2013-10-01 00:00:00')
```

If the given date *is* on an anchor point, it is moved `|n|` points forwards or backwards.

```
In [245]: pd.Timestamp("2014-01-01") + pd.offsets.MonthBegin(n=1)
Out[245]: Timestamp('2014-02-01 00:00:00')

In [246]: pd.Timestamp("2014-01-31") + pd.offsets.MonthEnd(n=1)
Out[246]: Timestamp('2014-02-28 00:00:00')

In [247]: pd.Timestamp("2014-01-01") - pd.offsets.MonthBegin(n=1)
Out[247]: Timestamp('2013-12-01 00:00:00')

In [248]: pd.Timestamp("2014-01-31") - pd.offsets.MonthEnd(n=1)
Out[248]: Timestamp('2013-12-31 00:00:00')

In [249]: pd.Timestamp("2014-01-01") + pd.offsets.MonthBegin(n=4)
Out[249]: Timestamp('2014-05-01 00:00:00')

In [250]: pd.Timestamp("2014-01-31") - pd.offsets.MonthBegin(n=4)
Out[250]: Timestamp('2013-10-01 00:00:00')
```

For the case when `n=0`, the date is not moved if on an anchor point, otherwise it is rolled forward to the next anchor point.

```
In [251]: pd.Timestamp("2014-01-02") + pd.offsets.MonthBegin(n=0)
Out[251]: Timestamp('2014-02-01 00:00:00')

In [252]: pd.Timestamp("2014-01-02") + pd.offsets.MonthEnd(n=0)
Out[252]: Timestamp('2014-01-31 00:00:00')

In [253]: pd.Timestamp("2014-01-01") + pd.offsets.MonthBegin(n=0)
Out[253]: Timestamp('2014-01-01 00:00:00')

In [254]: pd.Timestamp("2014-01-31") + pd.offsets.MonthEnd(n=0)
Out[254]: Timestamp('2014-01-31 00:00:00')
```

Holidays / holiday calendars

Holidays and calendars provide a simple way to define holiday rules to be used with `CustomBusinessDay` or in other analysis that requires a predefined set of holidays. The `AbstractHolidayCalendar` class provides all the necessary methods to return a list of holidays and only `rules` need to be defined in a specific holiday calendar class. Furthermore, the `start_date` and `end_date` class attributes determine over what date range holidays are generated. These should be overwritten on the `AbstractHolidayCalendar` class to have the range apply to all calendar subclasses. `USFederalHolidayCalendar` is the only calendar that exists and primarily serves as an example for developing other calendars.

For holidays that occur on fixed dates (e.g., US Memorial Day or July 4th) an observance rule determines when that holiday is observed if it falls on a weekend or some other non-observed day. Defined observance rules are:

Rule	Description
nearest_workday	move Saturday to Friday and Sunday to Monday
sunday_to_monday	move Sunday to following Monday
next_monday_or_tuesday	move Saturday to Monday and Sunday/Monday to Tuesday
previous_friday	move Saturday and Sunday to previous Friday"
next_monday	move Saturday and Sunday to following Monday

An example of how holidays and holiday calendars are defined:

```
In [255]: from pandas.tseries.holiday import (
   .....:     Holiday,
   .....:     USMemorialDay,
   .....:     AbstractHolidayCalendar,
   .....:     nearest_workday,
   .....:     MO,
   .....: )
   .....:

In [256]: class ExampleCalendar(AbstractHolidayCalendar):
   .....:     rules = [
   .....:         USMemorialDay,
   .....:         Holiday("July 4th", month=7, day=4, observance=nearest_workday),
   .....:         Holiday(
   .....:             "Columbus Day",
   .....:             month=10,
   .....:             day=1,
   .....:             offset=pd.DateOffset(weekday=MO(2)),
   .....:         ),
   .....:     ]
   .....:

In [257]: cal = ExampleCalendar()

In [258]: cal.holidays(datetime.datetime(2012, 1, 1), datetime.datetime(2012, 12, 31))
Out[258]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype=
↪'datetime64[ns]', freq=None)
```

hint **weekday=MO(2)** is same as **2 * Week(weekday=2)**

Using this calendar, creating an index or doing offset arithmetic skips weekends and holidays (i.e., Memorial Day/July 4th). For example, the below defines a custom business day offset using the `ExampleCalendar`. Like any other offset, it can be used to create a `DatetimeIndex` or added to `datetime` or `Timestamp` objects.

```
In [259]: pd.date_range(
   .....:     start="7/1/2012", end="7/10/2012", freq=pd.offsets.CDay(calendar=cal)
   .....: ).to_pydatetime()
   .....:
Out[259]:
array([datetime.datetime(2012, 7, 2, 0, 0),
       datetime.datetime(2012, 7, 3, 0, 0),
       datetime.datetime(2012, 7, 5, 0, 0),
       datetime.datetime(2012, 7, 6, 0, 0),
       datetime.datetime(2012, 7, 9, 0, 0),
       datetime.datetime(2012, 7, 10, 0, 0)], dtype=object)

In [260]: offset = pd.offsets.CustomBusinessDay(calendar=cal)

In [261]: datetime.datetime(2012, 5, 25) + offset
Out[261]: Timestamp('2012-05-29 00:00:00')

In [262]: datetime.datetime(2012, 7, 3) + offset
Out[262]: Timestamp('2012-07-05 00:00:00')

In [263]: datetime.datetime(2012, 7, 3) + 2 * offset
Out[263]: Timestamp('2012-07-06 00:00:00')
```

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```
In [264]: datetime.datetime(2012, 7, 6) + offset
Out[264]: Timestamp('2012-07-09 00:00:00')
```

Ranges are defined by the `start_date` and `end_date` class attributes of `AbstractHolidayCalendar`. The defaults are shown below.

```
In [265]: AbstractHolidayCalendar.start_date
Out[265]: Timestamp('1970-01-01 00:00:00')

In [266]: AbstractHolidayCalendar.end_date
Out[266]: Timestamp('2200-12-31 00:00:00')
```

These dates can be overwritten by setting the attributes as datetime/Timestamp/string.

```
In [267]: AbstractHolidayCalendar.start_date = datetime.datetime(2012, 1, 1)

In [268]: AbstractHolidayCalendar.end_date = datetime.datetime(2012, 12, 31)

In [269]: cal.holidays()
Out[269]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype=
↪'datetime64[ns]', freq=None)
```

Every calendar class is accessible by name using the `get_calendar` function which returns a holiday class instance. Any imported calendar class will automatically be available by this function. Also, `HolidayCalendarFactory` provides an easy interface to create calendars that are combinations of calendars or calendars with additional rules.

```
In [270]: from pandas.tseries.holiday import get_calendar, HolidayCalendarFactory,␣
↪USLaborDay

In [271]: cal = get_calendar("ExampleCalendar")

In [272]: cal.rules
Out[272]:
[Holiday: Memorial Day (month=5, day=31, offset=<DateOffset: weekday=MO(-1)>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at␣
↪0x7f709434c5e0>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: weekday=MO(+2)>)]

In [273]: new_cal = HolidayCalendarFactory("NewExampleCalendar", cal, USLaborDay)

In [274]: new_cal.rules
Out[274]:
[Holiday: Labor Day (month=9, day=1, offset=<DateOffset: weekday=MO(+1)>),
 Holiday: Memorial Day (month=5, day=31, offset=<DateOffset: weekday=MO(-1)>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at␣
↪0x7f709434c5e0>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: weekday=MO(+2)>)]
```

2.19.9 Time series-related instance methods

Shifting / lagging

One may want to *shift* or *lag* the values in a time series back and forward in time. The method for this is `shift()`, which is available on all of the pandas objects.

```
In [275]: ts = pd.Series(range(len(rng)), index=rng)

In [276]: ts = ts[:5]

In [277]: ts.shift(1)
Out[277]:
2012-01-01    NaN
2012-01-02    0.0
2012-01-03    1.0
Freq: D, dtype: float64
```

The `shift` method accepts an `freq` argument which can accept a `DateOffset` class or other `timedelta`-like object or also an *offset alias*.

When `freq` is specified, `shift` method changes all the dates in the index rather than changing the alignment of the data and the index:

```
In [278]: ts.shift(5, freq="D")
Out[278]:
2012-01-06    0
2012-01-07    1
2012-01-08    2
Freq: D, dtype: int64

In [279]: ts.shift(5, freq=pd.offsets.BDay())
Out[279]:
2012-01-06    0
2012-01-09    1
2012-01-10    2
dtype: int64

In [280]: ts.shift(5, freq="BM")
Out[280]:
2012-05-31    0
2012-05-31    1
2012-05-31    2
dtype: int64
```

Note that with when `freq` is specified, the leading entry is no longer NaN because the data is not being realigned.

Frequency conversion

The primary function for changing frequencies is the *asfreq()* method. For a DatetimeIndex, this is basically just a thin, but convenient wrapper around *reindex()* which generates a date_range and calls reindex.

```
In [281]: dr = pd.date_range("1/1/2010", periods=3, freq=3 * pd.offsets.BDay())

In [282]: ts = pd.Series(np.random.randn(3), index=dr)

In [283]: ts
Out[283]:
2010-01-01    1.494522
2010-01-06   -0.778425
2010-01-11   -0.253355
Freq: 3B, dtype: float64

In [284]: ts.asfreq(pd.offsets.BDay())
Out[284]:
2010-01-01    1.494522
2010-01-04         NaN
2010-01-05         NaN
2010-01-06   -0.778425
2010-01-07         NaN
2010-01-08         NaN
2010-01-11   -0.253355
Freq: B, dtype: float64
```

asfreq provides a further convenience so you can specify an interpolation method for any gaps that may appear after the frequency conversion.

```
In [285]: ts.asfreq(pd.offsets.BDay(), method="pad")
Out[285]:
2010-01-01    1.494522
2010-01-04    1.494522
2010-01-05    1.494522
2010-01-06   -0.778425
2010-01-07   -0.778425
2010-01-08   -0.778425
2010-01-11   -0.253355
Freq: B, dtype: float64
```

Filling forward / backward

Related to asfreq and reindex is *fillna()*, which is documented in the *missing data section*.

Converting to Python datetimes

DatetimeIndex can be converted to an array of Python native datetime.datetime objects using the to_pydatetime method.

2.19.10 Resampling

pandas has a simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications.

`resample()` is a time-based groupby, followed by a reduction method on each of its groups. See some *cookbook examples* for some advanced strategies.

The `resample()` method can be used directly from `DataFrameGroupBy` objects, see the *groupby docs*.

Basics

```
In [286]: rng = pd.date_range("1/1/2012", periods=100, freq="S")

In [287]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [288]: ts.resample("5Min").sum()
Out[288]:
2012-01-01    25103
Freq: 5T, dtype: int64
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

Any function available via *dispatching* is available as a method of the returned object, including `sum`, `mean`, `std`, `sem`, `max`, `min`, `median`, `first`, `last`, `ohlc`:

```
In [289]: ts.resample("5Min").mean()
Out[289]:
2012-01-01    251.03
Freq: 5T, dtype: float64

In [290]: ts.resample("5Min").ohlc()
Out[290]:
            open  high  low  close
2012-01-01   308   460    9    205

In [291]: ts.resample("5Min").max()
Out[291]:
2012-01-01    460
Freq: 5T, dtype: int64
```

For downsampling, `closed` can be set to 'left' or 'right' to specify which end of the interval is closed:

```
In [292]: ts.resample("5Min", closed="right").mean()
Out[292]:
2011-12-31 23:55:00    308.000000
2012-01-01 00:00:00    250.454545
Freq: 5T, dtype: float64

In [293]: ts.resample("5Min", closed="left").mean()
Out[293]:
2012-01-01    251.03
Freq: 5T, dtype: float64
```

Parameters like `label` are used to manipulate the resulting labels. `label` specifies whether the result is labeled with the beginning or the end of the interval.

```
In [294]: ts.resample("5Min").mean()  # by default label='left'
Out[294]:
2012-01-01    251.03
Freq: 5T, dtype: float64

In [295]: ts.resample("5Min", label="left").mean()
Out[295]:
2012-01-01    251.03
Freq: 5T, dtype: float64
```

Warning: The default values for `label` and `closed` is '**left**' for all frequency offsets except for 'M', 'A', 'Q', 'BM', 'BA', 'BQ', and 'W' which all have a default of 'right'.

This might unintendedly lead to looking ahead, where the value for a later time is pulled back to a previous time as in the following example with the *BusinessDay* frequency:

```
In [296]: s = pd.date_range("2000-01-01", "2000-01-05").to_series()

In [297]: s.iloc[2] = pd.NaT

In [298]: s.dt.day_name()
Out[298]:
2000-01-01     Saturday
2000-01-02       Sunday
2000-01-03          NaN
2000-01-04      Tuesday
2000-01-05    Wednesday
Freq: D, dtype: object

# default: label='left', closed='left'
In [299]: s.resample("B").last().dt.day_name()
Out[299]:
1999-12-31       Sunday
2000-01-03          NaN
2000-01-04      Tuesday
2000-01-05    Wednesday
Freq: B, dtype: object
```

Notice how the value for Sunday got pulled back to the previous Friday. To get the behavior where the value for Sunday is pushed to Monday, use instead

```
In [300]: s.resample("B", label="right", closed="right").last().dt.day_name()
Out[300]:
2000-01-03       Sunday
2000-01-04      Tuesday
2000-01-05    Wednesday
Freq: B, dtype: object
```

The `axis` parameter can be set to 0 or 1 and allows you to resample the specified axis for a `DataFrame`.

`kind` can be set to 'timestamp' or 'period' to convert the resulting index to/from timestamp and time span representations. By default `resample` retains the input representation.

`convention` can be set to 'start' or 'end' when resampling period data (detail below). It specifies how low frequency periods are converted to higher frequency periods.

Upsampling

For upsampling, you can specify a way to upsample and the `limit` parameter to interpolate over the gaps that are created:

```
# from secondly to every 250 milliseconds
In [301]: ts[:2].resample("250L").asfreq()
Out[301]:
2012-01-01 00:00:00.000    308.0
2012-01-01 00:00:00.250      NaN
2012-01-01 00:00:00.500      NaN
2012-01-01 00:00:00.750      NaN
2012-01-01 00:00:01.000    204.0
Freq: 250L, dtype: float64

In [302]: ts[:2].resample("250L").ffill()
Out[302]:
2012-01-01 00:00:00.000    308
2012-01-01 00:00:00.250    308
2012-01-01 00:00:00.500    308
2012-01-01 00:00:00.750    308
2012-01-01 00:00:01.000    204
Freq: 250L, dtype: int64

In [303]: ts[:2].resample("250L").ffill(limit=2)
Out[303]:
2012-01-01 00:00:00.000    308.0
2012-01-01 00:00:00.250    308.0
2012-01-01 00:00:00.500    308.0
2012-01-01 00:00:00.750      NaN
2012-01-01 00:00:01.000    204.0
Freq: 250L, dtype: float64
```

Sparse resampling

Sparse timeseries are the ones where you have a lot fewer points relative to the amount of time you are looking to resample. Naively upsampling a sparse series can potentially generate lots of intermediate values. When you don't want to use a method to fill these values, e.g. `fill_method` is `None`, then intermediate values will be filled with `NaN`.

Since `resample` is a time-based groupby, the following is a method to efficiently resample only the groups that are not all `NaN`.

```
In [304]: rng = pd.date_range("2014-1-1", periods=100, freq="D") + pd.Timedelta("1s")

In [305]: ts = pd.Series(range(100), index=rng)
```

If we want to resample to the full range of the series:

```
In [306]: ts.resample("3T").sum()
Out[306]:
2014-01-01 00:00:00     0
2014-01-01 00:03:00     0
2014-01-01 00:06:00     0
2014-01-01 00:09:00     0
2014-01-01 00:12:00     0
```

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```
                     ..
2014-04-09 23:48:00     0
2014-04-09 23:51:00     0
2014-04-09 23:54:00     0
2014-04-09 23:57:00     0
2014-04-10 00:00:00    99
Freq: 3T, Length: 47521, dtype: int64
```

We can instead only resample those groups where we have points as follows:

```
In [307]: from functools import partial

In [308]: from pandas.tseries.frequencies import to_offset

In [309]: def round(t, freq):
   .....:     freq = to_offset(freq)
   .....:     return pd.Timestamp((t.value // freq.delta.value) * freq.delta.value)
   .....:

In [310]: ts.groupby(partial(round, freq="3T")).sum()
Out[310]:
2014-01-01     0
2014-01-02     1
2014-01-03     2
2014-01-04     3
2014-01-05     4
              ..
2014-04-06    95
2014-04-07    96
2014-04-08    97
2014-04-09    98
2014-04-10    99
Length: 100, dtype: int64
```

Aggregation

Similar to the *aggregating API*, *groupby API*, and the *window API*, a `Resampler` can be selectively resampled.

Resampling a `DataFrame`, the default will be to act on all columns with the same function.

```
In [311]: df = pd.DataFrame(
   .....:     np.random.randn(1000, 3),
   .....:     index=pd.date_range("1/1/2012", freq="S", periods=1000),
   .....:     columns=["A", "B", "C"],
   .....: )
   .....:

In [312]: r = df.resample("3T")

In [313]: r.mean()
Out[313]:
                            A         B         C
2012-01-01 00:00:00 -0.033823 -0.121514 -0.081447
2012-01-01 00:03:00  0.056909  0.146731 -0.024320
2012-01-01 00:06:00 -0.058837  0.047046 -0.052021
```

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```
2012-01-01 00:09:00  0.063123 -0.026158 -0.066533
2012-01-01 00:12:00  0.186340 -0.003144  0.074752
2012-01-01 00:15:00 -0.085954 -0.016287 -0.050046
```

We can select a specific column or columns using standard getitem.

```
In [314]: r["A"].mean()
Out[314]:
2012-01-01 00:00:00   -0.033823
2012-01-01 00:03:00    0.056909
2012-01-01 00:06:00   -0.058837
2012-01-01 00:09:00    0.063123
2012-01-01 00:12:00    0.186340
2012-01-01 00:15:00   -0.085954
Freq: 3T, Name: A, dtype: float64

In [315]: r[["A", "B"]].mean()
Out[315]:
                            A         B
2012-01-01 00:00:00 -0.033823 -0.121514
2012-01-01 00:03:00  0.056909  0.146731
2012-01-01 00:06:00 -0.058837  0.047046
2012-01-01 00:09:00  0.063123 -0.026158
2012-01-01 00:12:00  0.186340 -0.003144
2012-01-01 00:15:00 -0.085954 -0.016287
```

You can pass a list or dict of functions to do aggregation with, outputting a `DataFrame`:

```
In [316]: r["A"].agg([np.sum, np.mean, np.std])
Out[316]:
                           sum      mean       std
2012-01-01 00:00:00  -6.088060 -0.033823  1.043263
2012-01-01 00:03:00  10.243678  0.056909  1.058534
2012-01-01 00:06:00 -10.590584 -0.058837  0.949264
2012-01-01 00:09:00  11.362228  0.063123  1.028096
2012-01-01 00:12:00  33.541257  0.186340  0.884586
2012-01-01 00:15:00  -8.595393 -0.085954  1.035476
```

On a resampled `DataFrame`, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [317]: r.agg([np.sum, np.mean])
Out[317]:
                            A                    B                    C
                          sum      mean        sum      mean        sum      mean
2012-01-01 00:00:00  -6.088060 -0.033823 -21.872530 -0.121514 -14.660515 -0.081447
2012-01-01 00:03:00  10.243678  0.056909  26.411633  0.146731  -4.377642 -0.024320
2012-01-01 00:06:00 -10.590584 -0.058837   8.468289  0.047046  -9.363825 -0.052021
2012-01-01 00:09:00  11.362228  0.063123  -4.708526 -0.026158 -11.975895 -0.066533
2012-01-01 00:12:00  33.541257  0.186340  -0.565895 -0.003144  13.455299  0.074752
2012-01-01 00:15:00  -8.595393 -0.085954  -1.628689 -0.016287  -5.004580 -0.050046
```

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a `DataFrame`:

```
In [318]: r.agg({"A": np.sum, "B": lambda x: np.std(x, ddof=1)})
Out[318]:
```

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```
                            A         B
2012-01-01 00:00:00  -6.088060  1.001294
2012-01-01 00:03:00  10.243678  1.074597
2012-01-01 00:06:00 -10.590584  0.987309
2012-01-01 00:09:00  11.362228  0.944953
2012-01-01 00:12:00  33.541257  1.095025
2012-01-01 00:15:00  -8.595393  1.035312
```

The function names can also be strings. In order for a string to be valid it must be implemented on the resampled object:

```
In [319]: r.agg({"A": "sum", "B": "std"})
Out[319]:
                            A         B
2012-01-01 00:00:00  -6.088060  1.001294
2012-01-01 00:03:00  10.243678  1.074597
2012-01-01 00:06:00 -10.590584  0.987309
2012-01-01 00:09:00  11.362228  0.944953
2012-01-01 00:12:00  33.541257  1.095025
2012-01-01 00:15:00  -8.595393  1.035312
```

Furthermore, you can also specify multiple aggregation functions for each column separately.

```
In [320]: r.agg({"A": ["sum", "std"], "B": ["mean", "std"]})
Out[320]:
                            A                   B
                          sum       std      mean       std
2012-01-01 00:00:00  -6.088060  1.043263 -0.121514  1.001294
2012-01-01 00:03:00  10.243678  1.058534  0.146731  1.074597
2012-01-01 00:06:00 -10.590584  0.949264  0.047046  0.987309
2012-01-01 00:09:00  11.362228  1.028096 -0.026158  0.944953
2012-01-01 00:12:00  33.541257  0.884586 -0.003144  1.095025
2012-01-01 00:15:00  -8.595393  1.035476 -0.016287  1.035312
```

If a `DataFrame` does not have a datetimelike index, but instead you want to resample based on datetimelike column in the frame, it can passed to the `on` keyword.

```
In [321]: df = pd.DataFrame(
   .....:     {"date": pd.date_range("2015-01-01", freq="W", periods=5), "a": np.
↪arange(5)},
   .....:     index=pd.MultiIndex.from_arrays(
   .....:         [[1, 2, 3, 4, 5], pd.date_range("2015-01-01", freq="W", periods=5)],
   .....:         names=["v", "d"],
   .....:     ),
   .....: )
   .....:

In [322]: df
Out[322]:
                 date  a
v d
1 2015-01-04 2015-01-04  0
2 2015-01-11 2015-01-11  1
3 2015-01-18 2015-01-18  2
4 2015-01-25 2015-01-25  3
5 2015-02-01 2015-02-01  4
```

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```
In [323]: df.resample("M", on="date").sum()
Out[323]:
            a
date
2015-01-31  6
2015-02-28  4
```

Similarly, if you instead want to resample by a datetimelike level of `MultiIndex`, its name or location can be passed to the `level` keyword.

```
In [324]: df.resample("M", level="d").sum()
Out[324]:
            a
d
2015-01-31  6
2015-02-28  4
```

Iterating through groups

With the `Resampler` object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby()`:

```
In [325]: small = pd.Series(
   .....:     range(6),
   .....:     index=pd.to_datetime(
   .....:         [
   .....:             "2017-01-01T00:00:00",
   .....:             "2017-01-01T00:30:00",
   .....:             "2017-01-01T00:31:00",
   .....:             "2017-01-01T01:00:00",
   .....:             "2017-01-01T03:00:00",
   .....:             "2017-01-01T03:05:00",
   .....:         ]
   .....:     ),
   .....: )
   .....:

In [326]: resampled = small.resample("H")

In [327]: for name, group in resampled:
   .....:     print("Group: ", name)
   .....:     print("-" * 27)
   .....:     print(group, end="\n\n")
   .....:
Group:  2017-01-01 00:00:00
---------------------------
2017-01-01 00:00:00    0
2017-01-01 00:30:00    1
2017-01-01 00:31:00    2
dtype: int64

Group:  2017-01-01 01:00:00
---------------------------
2017-01-01 01:00:00    3
```

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```
dtype: int64

Group:  2017-01-01 02:00:00
----------------------------
Series([], dtype: int64)

Group:  2017-01-01 03:00:00
----------------------------
2017-01-01 03:00:00    4
2017-01-01 03:05:00    5
dtype: int64
```

See *Iterating through groups* or `Resampler.__iter__` for more.

Use `origin` or `offset` to adjust the start of the bins

New in version 1.1.0.

The bins of the grouping are adjusted based on the beginning of the day of the time series starting point. This works well with frequencies that are multiples of a day (like `30D`) or that divide a day evenly (like `90s` or `1min`). This can create inconsistencies with some frequencies that do not meet this criteria. To change this behavior you can specify a fixed Timestamp with the argument `origin`.

For example:

```
In [328]: start, end = "2000-10-01 23:30:00", "2000-10-02 00:30:00"

In [329]: middle = "2000-10-02 00:00:00"

In [330]: rng = pd.date_range(start, end, freq="7min")

In [331]: ts = pd.Series(np.arange(len(rng)) * 3, index=rng)

In [332]: ts
Out[332]:
2000-10-01 23:30:00     0
2000-10-01 23:37:00     3
2000-10-01 23:44:00     6
2000-10-01 23:51:00     9
2000-10-01 23:58:00    12
2000-10-02 00:05:00    15
2000-10-02 00:12:00    18
2000-10-02 00:19:00    21
2000-10-02 00:26:00    24
Freq: 7T, dtype: int64
```

Here we can see that, when using `origin` with its default value (`'start_day'`), the result after `'2000-10-02 00:00:00'` are not identical depending on the start of time series:

```
In [333]: ts.resample("17min", origin="start_day").sum()
Out[333]:
2000-10-01 23:14:00     0
2000-10-01 23:31:00     9
2000-10-01 23:48:00    21
2000-10-02 00:05:00    54
2000-10-02 00:22:00    24
```

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```
Freq: 17T, dtype: int64

In [334]: ts[middle:end].resample("17min", origin="start_day").sum()
Out[334]:
2000-10-02 00:00:00    33
2000-10-02 00:17:00    45
Freq: 17T, dtype: int64
```

Here we can see that, when setting `origin` to `'epoch'`, the result after `'2000-10-02 00:00:00'` are identical depending on the start of time series:

```
In [335]: ts.resample("17min", origin="epoch").sum()
Out[335]:
2000-10-01 23:18:00     0
2000-10-01 23:35:00    18
2000-10-01 23:52:00    27
2000-10-02 00:09:00    39
2000-10-02 00:26:00    24
Freq: 17T, dtype: int64

In [336]: ts[middle:end].resample("17min", origin="epoch").sum()
Out[336]:
2000-10-01 23:52:00    15
2000-10-02 00:09:00    39
2000-10-02 00:26:00    24
Freq: 17T, dtype: int64
```

If needed you can use a custom timestamp for `origin`:

```
In [337]: ts.resample("17min", origin="2001-01-01").sum()
Out[337]:
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64

In [338]: ts[middle:end].resample("17min", origin=pd.Timestamp("2001-01-01")).sum()
Out[338]:
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

If needed you can just adjust the bins with an `offset` Timedelta that would be added to the default `origin`. Those two examples are equivalent for this time series:

```
In [339]: ts.resample("17min", origin="start").sum()
Out[339]:
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64

In [340]: ts.resample("17min", offset="23h30min").sum()
Out[340]:
```

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```
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

Note the use of `'start'` for `origin` on the last example. In that case, `origin` will be set to the first value of the timeseries.

2.19.11 Time span representation

Regular intervals of time are represented by `Period` objects in pandas while sequences of `Period` objects are collected in a `PeriodIndex`, which can be created with the convenience function `period_range`.

Period

A `Period` represents a span of time (e.g., a day, a month, a quarter, etc). You can specify the span via `freq` keyword using a frequency alias like below. Because `freq` represents a span of `Period`, it cannot be negative like "-3D".

```
In [341]: pd.Period("2012", freq="A-DEC")
Out[341]: Period('2012', 'A-DEC')

In [342]: pd.Period("2012-1-1", freq="D")
Out[342]: Period('2012-01-01', 'D')

In [343]: pd.Period("2012-1-1 19:00", freq="H")
Out[343]: Period('2012-01-01 19:00', 'H')

In [344]: pd.Period("2012-1-1 19:00", freq="5H")
Out[344]: Period('2012-01-01 19:00', '5H')
```

Adding and subtracting integers from periods shifts the period by its own frequency. Arithmetic is not allowed between `Period` with different `freq` (span).

```
In [345]: p = pd.Period("2012", freq="A-DEC")

In [346]: p + 1
Out[346]: Period('2013', 'A-DEC')

In [347]: p - 3
Out[347]: Period('2009', 'A-DEC')

In [348]: p = pd.Period("2012-01", freq="2M")

In [349]: p + 2
Out[349]: Period('2012-05', '2M')

In [350]: p - 1
Out[350]: Period('2011-11', '2M')

In [351]: p == pd.Period("2012-01", freq="3M")
---------------------------------------------------------------------------
IncompatibleFrequency                     Traceback (most recent call last)
<ipython-input-351-747e98b17e20> in <module>
```

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```
----> 1 p == pd.Period("2012-01", freq="3M")

/pandas/pandas/_libs/tslibs/period.pyx in pandas._libs.tslibs.period._Period.__
↪richcmp__()

IncompatibleFrequency: Input has different freq=3M from Period(freq=2M)
```

If `Period` freq is daily or higher (`D`, `H`, `T`, `S`, `L`, `U`, `N`), `offsets` and `timedelta`-like can be added if the result can have the same freq. Otherwise, `ValueError` will be raised.

```
In [352]: p = pd.Period("2014-07-01 09:00", freq="H")

In [353]: p + pd.offsets.Hour(2)
Out[353]: Period('2014-07-01 11:00', 'H')

In [354]: p + datetime.timedelta(minutes=120)
Out[354]: Period('2014-07-01 11:00', 'H')

In [355]: p + np.timedelta64(7200, "s")
Out[355]: Period('2014-07-01 11:00', 'H')
```

```
In [1]: p + pd.offsets.Minute(5)
Traceback
   ...
ValueError: Input has different freq from Period(freq=H)
```

If `Period` has other frequencies, only the same `offsets` can be added. Otherwise, `ValueError` will be raised.

```
In [356]: p = pd.Period("2014-07", freq="M")

In [357]: p + pd.offsets.MonthEnd(3)
Out[357]: Period('2014-10', 'M')
```

```
In [1]: p + pd.offsets.MonthBegin(3)
Traceback
   ...
ValueError: Input has different freq from Period(freq=M)
```

Taking the difference of `Period` instances with the same frequency will return the number of frequency units between them:

```
In [358]: pd.Period("2012", freq="A-DEC") - pd.Period("2002", freq="A-DEC")
Out[358]: <10 * YearEnds: month=12>
```

PeriodIndex and period_range

Regular sequences of `Period` objects can be collected in a `PeriodIndex`, which can be constructed using the `period_range` convenience function:

```
In [359]: prng = pd.period_range("1/1/2011", "1/1/2012", freq="M")

In [360]: prng
Out[360]:
PeriodIndex(['2011-01', '2011-02', '2011-03', '2011-04', '2011-05', '2011-06',
```

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```
               '2011-07', '2011-08', '2011-09', '2011-10', '2011-11', '2011-12',
               '2012-01'],
              dtype='period[M]', freq='M')
```

The `PeriodIndex` constructor can also be used directly:

```
In [361]: pd.PeriodIndex(["2011-1", "2011-2", "2011-3"], freq="M")
Out[361]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')
```

Passing multiplied frequency outputs a sequence of `Period` which has multiplied span.

```
In [362]: pd.period_range(start="2014-01", freq="3M", periods=4)
Out[362]: PeriodIndex(['2014-01', '2014-04', '2014-07', '2014-10'], dtype='period[3M]
↪', freq='3M')
```

If `start` or `end` are `Period` objects, they will be used as anchor endpoints for a `PeriodIndex` with frequency matching that of the `PeriodIndex` constructor.

```
In [363]: pd.period_range(
   .....:     start=pd.Period("2017Q1", freq="Q"), end=pd.Period("2017Q2", freq="Q"),␣
↪freq="M"
   .....: )
   .....:
Out[363]: PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'], dtype='period[M]',
↪ freq='M')
```

Just like `DatetimeIndex`, a `PeriodIndex` can also be used to index pandas objects:

```
In [364]: ps = pd.Series(np.random.randn(len(prng)), prng)

In [365]: ps
Out[365]:
2011-01   -2.916901
2011-02    0.514474
2011-03    1.346470
2011-04    0.816397
2011-05    2.258648
2011-06    0.494789
2011-07    0.301239
2011-08    0.464776
2011-09   -1.393581
2011-10    0.056780
2011-11    0.197035
2011-12    2.261385
2012-01   -0.329583
Freq: M, dtype: float64
```

`PeriodIndex` supports addition and subtraction with the same rule as `Period`.

```
In [366]: idx = pd.period_range("2014-07-01 09:00", periods=5, freq="H")

In [367]: idx
Out[367]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
             '2014-07-01 12:00', '2014-07-01 13:00'],
            dtype='period[H]', freq='H')
```

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```
In [368]: idx + pd.offsets.Hour(2)
Out[368]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='period[H]', freq='H')

In [369]: idx = pd.period_range("2014-07", periods=5, freq="M")

In [370]: idx
Out[370]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'], dtype=
↪'period[M]', freq='M')

In [371]: idx + pd.offsets.MonthEnd(3)
Out[371]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'], dtype=
↪'period[M]', freq='M')
```

`PeriodIndex` has its own dtype named `period`, refer to *Period Dtypes*.

Period dtypes

`PeriodIndex` has a custom `period` dtype. This is a pandas extension dtype similar to the *timezone aware dtype* (`datetime64[ns, tz]`).

The `period` dtype holds the `freq` attribute and is represented with `period[freq]` like `period[D]` or `period[M]`, using *frequency strings*.

```
In [372]: pi = pd.period_range("2016-01-01", periods=3, freq="M")

In [373]: pi
Out[373]: PeriodIndex(['2016-01', '2016-02', '2016-03'], dtype='period[M]', freq='M')

In [374]: pi.dtype
Out[374]: period[M]
```

The `period` dtype can be used in `.astype(...)`. It allows one to change the `freq` of a `PeriodIndex` like `.asfreq()` and convert a `DatetimeIndex` to `PeriodIndex` like `to_period()`:

```
# change monthly freq to daily freq
In [375]: pi.astype("period[D]")
Out[375]: PeriodIndex(['2016-01-31', '2016-02-29', '2016-03-31'], dtype='period[D]',␣
↪freq='D')

# convert to DatetimeIndex
In [376]: pi.astype("datetime64[ns]")
Out[376]: DatetimeIndex(['2016-01-01', '2016-02-01', '2016-03-01'], dtype=
↪'datetime64[ns]', freq='MS')

# convert to PeriodIndex
In [377]: dti = pd.date_range("2011-01-01", freq="M", periods=3)

In [378]: dti
Out[378]: DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31'], dtype=
↪'datetime64[ns]', freq='M')
```

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```
In [379]: dti.astype("period[M]")
Out[379]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')
```

PeriodIndex partial string indexing

PeriodIndex now supports partial string slicing with non-monotonic indexes.

New in version 1.1.0.

You can pass in dates and strings to `Series` and `DataFrame` with `PeriodIndex`, in the same manner as `DatetimeIndex`. For details, refer to *DatetimeIndex Partial String Indexing*.

```
In [380]: ps["2011-01"]
Out[380]: -2.9169013294054507

In [381]: ps[datetime.datetime(2011, 12, 25):]
Out[381]:
2011-12    2.261385
2012-01   -0.329583
Freq: M, dtype: float64

In [382]: ps["10/31/2011":"12/31/2011"]
Out[382]:
2011-10    0.056780
2011-11    0.197035
2011-12    2.261385
Freq: M, dtype: float64
```

Passing a string representing a lower frequency than `PeriodIndex` returns partial sliced data.

```
In [383]: ps["2011"]
Out[383]:
2011-01   -2.916901
2011-02    0.514474
2011-03    1.346470
2011-04    0.816397
2011-05    2.258648
2011-06    0.494789
2011-07    0.301239
2011-08    0.464776
2011-09   -1.393581
2011-10    0.056780
2011-11    0.197035
2011-12    2.261385
Freq: M, dtype: float64

In [384]: dfp = pd.DataFrame(
   .....:     np.random.randn(600, 1),
   .....:     columns=["A"],
   .....:     index=pd.period_range("2013-01-01 9:00", periods=600, freq="T"),
   .....: )
   .....:

In [385]: dfp
Out[385]:
                         A
```

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```
2013-01-01 09:00 -0.538468
2013-01-01 09:01 -1.365819
2013-01-01 09:02 -0.969051
2013-01-01 09:03 -0.331152
2013-01-01 09:04 -0.245334
...                    ...
2013-01-01 18:55  0.522460
2013-01-01 18:56  0.118710
2013-01-01 18:57  0.167517
2013-01-01 18:58  0.922883
2013-01-01 18:59  1.721104

[600 rows x 1 columns]
```

```
In [386]: dfp.loc["2013-01-01 10H"]
Out[386]:
                           A
2013-01-01 10:00 -0.308975
2013-01-01 10:01  0.542520
2013-01-01 10:02  1.061068
2013-01-01 10:03  0.754005
2013-01-01 10:04  0.352933
...                    ...
2013-01-01 10:55 -0.865621
2013-01-01 10:56 -1.167818
2013-01-01 10:57 -2.081748
2013-01-01 10:58 -0.527146
2013-01-01 10:59  0.802298

[60 rows x 1 columns]
```

As with `DatetimeIndex`, the endpoints will be included in the result. The example below slices data starting from 10:00 to 11:59.

```
In [387]: dfp["2013-01-01 10H":"2013-01-01 11H"]
Out[387]:
                           A
2013-01-01 10:00 -0.308975
2013-01-01 10:01  0.542520
2013-01-01 10:02  1.061068
2013-01-01 10:03  0.754005
2013-01-01 10:04  0.352933
...                    ...
2013-01-01 11:55 -0.590204
2013-01-01 11:56  1.539990
2013-01-01 11:57 -1.224826
2013-01-01 11:58  0.578798
2013-01-01 11:59 -0.685496

[120 rows x 1 columns]
```

Frequency conversion and resampling with PeriodIndex

The frequency of `Period` and `PeriodIndex` can be converted via the `asfreq` method. Let's start with the fiscal year 2011, ending in December:

```
In [388]: p = pd.Period("2011", freq="A-DEC")

In [389]: p
Out[389]: Period('2011', 'A-DEC')
```

We can convert it to a monthly frequency. Using the `how` parameter, we can specify whether to return the starting or ending month:

```
In [390]: p.asfreq("M", how="start")
Out[390]: Period('2011-01', 'M')

In [391]: p.asfreq("M", how="end")
Out[391]: Period('2011-12', 'M')
```

The shorthands 's' and 'e' are provided for convenience:

```
In [392]: p.asfreq("M", "s")
Out[392]: Period('2011-01', 'M')

In [393]: p.asfreq("M", "e")
Out[393]: Period('2011-12', 'M')
```

Converting to a "super-period" (e.g., annual frequency is a super-period of quarterly frequency) automatically returns the super-period that includes the input period:

```
In [394]: p = pd.Period("2011-12", freq="M")

In [395]: p.asfreq("A-NOV")
Out[395]: Period('2012', 'A-NOV')
```

Note that since we converted to an annual frequency that ends the year in November, the monthly period of December 2011 is actually in the 2012 A-NOV period.

Period conversions with anchored frequencies are particularly useful for working with various quarterly data common to economics, business, and other fields. Many organizations define quarters relative to the month in which their fiscal year starts and ends. Thus, first quarter of 2011 could start in 2010 or a few months into 2011. Via anchored frequencies, pandas works for all quarterly frequencies `Q-JAN` through `Q-DEC`.

`Q-DEC` define regular calendar quarters:

```
In [396]: p = pd.Period("2012Q1", freq="Q-DEC")

In [397]: p.asfreq("D", "s")
Out[397]: Period('2012-01-01', 'D')

In [398]: p.asfreq("D", "e")
Out[398]: Period('2012-03-31', 'D')
```

`Q-MAR` defines fiscal year end in March:

```
In [399]: p = pd.Period("2011Q4", freq="Q-MAR")

In [400]: p.asfreq("D", "s")
```

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```
Out[400]: Period('2011-01-01', 'D')

In [401]: p.asfreq("D", "e")
Out[401]: Period('2011-03-31', 'D')
```

2.19.12 Converting between representations

Timestamped data can be converted to PeriodIndex-ed data using `to_period` and vice-versa using `to_timestamp`:

```
In [402]: rng = pd.date_range("1/1/2012", periods=5, freq="M")

In [403]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [404]: ts
Out[404]:
2012-01-31    1.931253
2012-02-29   -0.184594
2012-03-31    0.249656
2012-04-30   -0.978151
2012-05-31   -0.873389
Freq: M, dtype: float64

In [405]: ps = ts.to_period()

In [406]: ps
Out[406]:
2012-01    1.931253
2012-02   -0.184594
2012-03    0.249656
2012-04   -0.978151
2012-05   -0.873389
Freq: M, dtype: float64

In [407]: ps.to_timestamp()
Out[407]:
2012-01-01    1.931253
2012-02-01   -0.184594
2012-03-01    0.249656
2012-04-01   -0.978151
2012-05-01   -0.873389
Freq: MS, dtype: float64
```

Remember that ‘s’ and ‘e’ can be used to return the timestamps at the start or end of the period:

```
In [408]: ps.to_timestamp("D", how="s")
Out[408]:
2012-01-01    1.931253
2012-02-01   -0.184594
2012-03-01    0.249656
2012-04-01   -0.978151
2012-05-01   -0.873389
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following

example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```
In [409]: prng = pd.period_range("1990Q1", "2000Q4", freq="Q-NOV")

In [410]: ts = pd.Series(np.random.randn(len(prng)), prng)

In [411]: ts.index = (prng.asfreq("M", "e") + 1).asfreq("H", "s") + 9

In [412]: ts.head()
Out[412]:
1990-03-01 09:00   -0.109291
1990-06-01 09:00   -0.637235
1990-09-01 09:00   -1.735925
1990-12-01 09:00    2.096946
1991-03-01 09:00   -1.039926
Freq: H, dtype: float64
```

2.19.13 Representing out-of-bounds spans

If you have data that is outside of the `Timestamp` bounds, see *Timestamp limitations*, then you can use a `PeriodIndex` and/or `Series` of `Periods` to do computations.

```
In [413]: span = pd.period_range("1215-01-01", "1381-01-01", freq="D")

In [414]: span
Out[414]:
PeriodIndex(['1215-01-01', '1215-01-02', '1215-01-03', '1215-01-04',
             '1215-01-05', '1215-01-06', '1215-01-07', '1215-01-08',
             '1215-01-09', '1215-01-10',
             ...
             '1380-12-23', '1380-12-24', '1380-12-25', '1380-12-26',
             '1380-12-27', '1380-12-28', '1380-12-29', '1380-12-30',
             '1380-12-31', '1381-01-01'],
            dtype='period[D]', length=60632, freq='D')
```

To convert from an `int64` based YYYYMMDD representation.

```
In [415]: s = pd.Series([20121231, 20141130, 99991231])

In [416]: s
Out[416]:
0    20121231
1    20141130
2    99991231
dtype: int64

In [417]: def conv(x):
   .....:     return pd.Period(year=x // 10000, month=x // 100 % 100, day=x % 100,␣
↪freq="D")
   .....:

In [418]: s.apply(conv)
Out[418]:
0    2012-12-31
1    2014-11-30
```

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```
2    9999-12-31
dtype: period[D]

In [419]: s.apply(conv)[2]
Out[419]: Period('9999-12-31', 'D')
```

These can easily be converted to a `PeriodIndex`:

```
In [420]: span = pd.PeriodIndex(s.apply(conv))

In [421]: span
Out[421]: PeriodIndex(['2012-12-31', '2014-11-30', '9999-12-31'], dtype='period[D]',␣
↪freq='D')
```

2.19.14 Time zone handling

pandas provides rich support for working with timestamps in different time zones using the `pytz` and `dateutil` libraries or `datetime.timezone` objects from the standard library.

Working with time zones

By default, pandas objects are time zone unaware:

```
In [422]: rng = pd.date_range("3/6/2012 00:00", periods=15, freq="D")

In [423]: rng.tz is None
Out[423]: True
```

To localize these dates to a time zone (assign a particular time zone to a naive date), you can use the `tz_localize` method or the `tz` keyword argument in *`date_range()`*, *`Timestamp`*, or *`DatetimeIndex`*. You can either pass `pytz` or `dateutil` time zone objects or Olson time zone database strings. Olson time zone strings will return `pytz` time zone objects by default. To return `dateutil` time zone objects, append `dateutil/` before the string.

- In `pytz` you can find a list of common (and less common) time zones using `from pytz import common_timezones, all_timezones`.
- `dateutil` uses the OS time zones so there isn't a fixed list available. For common zones, the names are the same as `pytz`.

```
In [424]: import dateutil

# pytz
In [425]: rng_pytz = pd.date_range("3/6/2012 00:00", periods=3, freq="D", tz="Europe/
↪London")

In [426]: rng_pytz.tz
Out[426]: <DstTzInfo 'Europe/London' LMT-1 day, 23:59:00 STD>

# dateutil
In [427]: rng_dateutil = pd.date_range("3/6/2012 00:00", periods=3, freq="D")

In [428]: rng_dateutil = rng_dateutil.tz_localize("dateutil/Europe/London")

In [429]: rng_dateutil.tz
```

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```
Out[429]: tzfile('/usr/share/zoneinfo/Europe/London')

# dateutil - utc special case
In [430]: rng_utc = pd.date_range(
   .....:     "3/6/2012 00:00",
   .....:     periods=3,
   .....:     freq="D",
   .....:     tz=dateutil.tz.tzutc(),
   .....: )
   .....:

In [431]: rng_utc.tz
Out[431]: tzutc()
```

New in version 0.25.0.

```
# datetime.timezone
In [432]: rng_utc = pd.date_range(
   .....:     "3/6/2012 00:00",
   .....:     periods=3,
   .....:     freq="D",
   .....:     tz=datetime.timezone.utc,
   .....: )
   .....:

In [433]: rng_utc.tz
Out[433]: datetime.timezone.utc
```

Note that the `UTC` time zone is a special case in `dateutil` and should be constructed explicitly as an instance of `dateutil.tz.tzutc`. You can also construct other time zones objects explicitly first.

```
In [434]: import pytz

# pytz
In [435]: tz_pytz = pytz.timezone("Europe/London")

In [436]: rng_pytz = pd.date_range("3/6/2012 00:00", periods=3, freq="D")

In [437]: rng_pytz = rng_pytz.tz_localize(tz_pytz)

In [438]: rng_pytz.tz == tz_pytz
Out[438]: True

# dateutil
In [439]: tz_dateutil = dateutil.tz.gettz("Europe/London")

In [440]: rng_dateutil = pd.date_range("3/6/2012 00:00", periods=3, freq="D", tz=tz_
↪dateutil)

In [441]: rng_dateutil.tz == tz_dateutil
Out[441]: True
```

To convert a time zone aware pandas object from one time zone to another, you can use the `tz_convert` method.

```
In [442]: rng_pytz.tz_convert("US/Eastern")
Out[442]:
```

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```
DatetimeIndex(['2012-03-05 19:00:00-05:00', '2012-03-06 19:00:00-05:00',
               '2012-03-07 19:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

Note: When using `pytz` time zones, *DatetimeIndex* will construct a different time zone object than a *Timestamp* for the same time zone input. A *DatetimeIndex* can hold a collection of *Timestamp* objects that may have different UTC offsets and cannot be succinctly represented by one `pytz` time zone instance while one *Timestamp* represents one point in time with a specific UTC offset.

```
In [443]: dti = pd.date_range("2019-01-01", periods=3, freq="D", tz="US/Pacific")

In [444]: dti.tz
Out[444]: <DstTzInfo 'US/Pacific' LMT-1 day, 16:07:00 STD>

In [445]: ts = pd.Timestamp("2019-01-01", tz="US/Pacific")

In [446]: ts.tz
Out[446]: <DstTzInfo 'US/Pacific' PST-1 day, 16:00:00 STD>
```

Warning: Be wary of conversions between libraries. For some time zones, `pytz` and `dateutil` have different definitions of the zone. This is more of a problem for unusual time zones than for 'standard' zones like `US/Eastern`.

Warning: Be aware that a time zone definition across versions of time zone libraries may not be considered equal. This may cause problems when working with stored data that is localized using one version and operated on with a different version. See *here* for how to handle such a situation.

Warning: For `pytz` time zones, it is incorrect to pass a time zone object directly into the `datetime.datetime` constructor (e.g., `datetime.datetime(2011, 1, 1, tz=pytz.timezone('US/Eastern'))`. Instead, the datetime needs to be localized using the `localize` method on the `pytz` time zone object.

Warning: Be aware that for times in the future, correct conversion between time zones (and UTC) cannot be guaranteed by any time zone library because a timezone's offset from UTC may be changed by the respective government.

Warning: If you are using dates beyond 2038-01-18, due to current deficiencies in the underlying libraries caused by the year 2038 problem, daylight saving time (DST) adjustments to timezone aware dates will not be applied. If and when the underlying libraries are fixed, the DST transitions will be applied.

For example, for two dates that are in British Summer Time (and so would normally be GMT+1), both the following asserts evaluate as true:

```
In [447]: d_2037 = "2037-03-31T010101"
```

```
In [448]: d_2038 = "2038-03-31T010101"

In [449]: DST = "Europe/London"

In [450]: assert pd.Timestamp(d_2037, tz=DST) != pd.Timestamp(d_2037, tz="GMT")

In [451]: assert pd.Timestamp(d_2038, tz=DST) == pd.Timestamp(d_2038, tz="GMT")
```

Under the hood, all timestamps are stored in UTC. Values from a time zone aware *DatetimeIndex* or *Timestamp* will have their fields (day, hour, minute, etc.) localized to the time zone. However, timestamps with the same UTC value are still considered to be equal even if they are in different time zones:

```
In [452]: rng_eastern = rng_utc.tz_convert("US/Eastern")

In [453]: rng_berlin = rng_utc.tz_convert("Europe/Berlin")

In [454]: rng_eastern[2]
Out[454]: Timestamp('2012-03-07 19:00:00-0500', tz='US/Eastern', freq='D')

In [455]: rng_berlin[2]
Out[455]: Timestamp('2012-03-08 01:00:00+0100', tz='Europe/Berlin', freq='D')

In [456]: rng_eastern[2] == rng_berlin[2]
Out[456]: True
```

Operations between *Series* in different time zones will yield UTC *Series*, aligning the data on the UTC timestamps:

```
In [457]: ts_utc = pd.Series(range(3), pd.date_range("20130101", periods=3, tz="UTC"))

In [458]: eastern = ts_utc.tz_convert("US/Eastern")

In [459]: berlin = ts_utc.tz_convert("Europe/Berlin")

In [460]: result = eastern + berlin

In [461]: result
Out[461]:
2013-01-01 00:00:00+00:00    0
2013-01-02 00:00:00+00:00    2
2013-01-03 00:00:00+00:00    4
Freq: D, dtype: int64

In [462]: result.index
Out[462]:
DatetimeIndex(['2013-01-01 00:00:00+00:00', '2013-01-02 00:00:00+00:00',
               '2013-01-03 00:00:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='D')
```

To remove time zone information, use `tz_localize(None)` or `tz_convert(None).tz_localize(None)` will remove the time zone yielding the local time representation. `tz_convert(None)` will remove the time zone after converting to UTC time.

```
In [463]: didx = pd.date_range(start="2014-08-01 09:00", freq="H", periods=3, tz="US/
↪Eastern")
```

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```
In [464]: didx
Out[464]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
               '2014-08-01 11:00:00-04:00'],
              dtype='datetime64[ns, US/Eastern]', freq='H')

In [465]: didx.tz_localize(None)
Out[465]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
               '2014-08-01 11:00:00'],
              dtype='datetime64[ns]', freq=None)

In [466]: didx.tz_convert(None)
Out[466]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00'],
              dtype='datetime64[ns]', freq='H')

# tz_convert(None) is identical to tz_convert('UTC').tz_localize(None)
In [467]: didx.tz_convert("UTC").tz_localize(None)
Out[467]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Fold

New in version 1.1.0.

For ambiguous times, pandas supports explicitly specifying the keyword-only fold argument. Due to daylight saving time, one wall clock time can occur twice when shifting from summer to winter time; fold describes whether the datetime-like corresponds to the first (0) or the second time (1) the wall clock hits the ambiguous time. Fold is supported only for constructing from naive `datetime.datetime` (see datetime documentation for details) or from *`Timestamp`* or for constructing from components (see below). Only `dateutil` timezones are supported (see dateutil documentation for `dateutil` methods that deal with ambiguous datetimes) as `pytz` timezones do not support fold (see pytz documentation for details on how `pytz` deals with ambiguous datetimes). To localize an ambiguous datetime with `pytz`, please use *`Timestamp.tz_localize()`*. In general, we recommend to rely on *`Timestamp.tz_localize()`* when localizing ambiguous datetimes if you need direct control over how they are handled.

```
In [468]: pd.Timestamp(
   .....:     datetime.datetime(2019, 10, 27, 1, 30, 0, 0),
   .....:     tz="dateutil/Europe/London",
   .....:     fold=0,
   .....: )
   .....:
Out[468]: Timestamp('2019-10-27 01:30:00+0100', tz='dateutil//usr/share/zoneinfo/
↪Europe/London')

In [469]: pd.Timestamp(
   .....:     year=2019,
   .....:     month=10,
   .....:     day=27,
   .....:     hour=1,
   .....:     minute=30,
```

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```
   .....:     tz="dateutil/Europe/London",
   .....:     fold=1,
   .....: )
   .....:
Out[469]: Timestamp('2019-10-27 01:30:00+0000', tz='dateutil//usr/share/zoneinfo/
↪Europe/London')
```

Ambiguous times when localizing

`tz_localize` may not be able to determine the UTC offset of a timestamp because daylight savings time (DST) in a local time zone causes some times to occur twice within one day ("clocks fall back"). The following options are available:

- `'raise'`: Raises a `pytz.AmbiguousTimeError` (the default behavior)
- `'infer'`: Attempt to determine the correct offset base on the monotonicity of the timestamps
- `'NaT'`: Replaces ambiguous times with `NaT`
- `bool`: `True` represents a DST time, `False` represents non-DST time. An array-like of `bool` values is supported for a sequence of times.

```
In [470]: rng_hourly = pd.DatetimeIndex(
   .....:     ["11/06/2011 00:00", "11/06/2011 01:00", "11/06/2011 01:00", "11/06/
↪2011 02:00"]
   .....: )
   .....:
```

This will fail as there are ambiguous times (`'11/06/2011 01:00'`)

```
In [2]: rng_hourly.tz_localize('US/Eastern')
AmbiguousTimeError: Cannot infer dst time from Timestamp('2011-11-06 01:00:00'), try␣
↪using the 'ambiguous' argument
```

Handle these ambiguous times by specifying the following.

```
In [471]: rng_hourly.tz_localize("US/Eastern", ambiguous="infer")
Out[471]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', '2011-11-06 01:00:00-04:00',
               '2011-11-06 01:00:00-05:00', '2011-11-06 02:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)

In [472]: rng_hourly.tz_localize("US/Eastern", ambiguous="NaT")
Out[472]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', 'NaT', 'NaT',
               '2011-11-06 02:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)

In [473]: rng_hourly.tz_localize("US/Eastern", ambiguous=[True, True, False, False])
Out[473]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', '2011-11-06 01:00:00-04:00',
               '2011-11-06 01:00:00-05:00', '2011-11-06 02:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

Nonexistent times when localizing

A DST transition may also shift the local time ahead by 1 hour creating nonexistent local times ("clocks spring forward"). The behavior of localizing a timeseries with nonexistent times can be controlled by the `nonexistent` argument. The following options are available:

- `'raise'`: Raises a `pytz.NonExistentTimeError` (the default behavior)
- `'NaT'`: Replaces nonexistent times with `NaT`
- `'shift_forward'`: Shifts nonexistent times forward to the closest real time
- `'shift_backward'`: Shifts nonexistent times backward to the closest real time
- timedelta object: Shifts nonexistent times by the timedelta duration

```
In [474]: dti = pd.date_range(start="2015-03-29 02:30:00", periods=3, freq="H")

# 2:30 is a nonexistent time
```

Localization of nonexistent times will raise an error by default.

```
In [2]: dti.tz_localize('Europe/Warsaw')
NonExistentTimeError: 2015-03-29 02:30:00
```

Transform nonexistent times to `NaT` or shift the times.

```
In [475]: dti
Out[475]:
DatetimeIndex(['2015-03-29 02:30:00', '2015-03-29 03:30:00',
               '2015-03-29 04:30:00'],
              dtype='datetime64[ns]', freq='H')

In [476]: dti.tz_localize("Europe/Warsaw", nonexistent="shift_forward")
Out[476]:
DatetimeIndex(['2015-03-29 03:00:00+02:00', '2015-03-29 03:30:00+02:00',
               '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)

In [477]: dti.tz_localize("Europe/Warsaw", nonexistent="shift_backward")
Out[477]:
DatetimeIndex(['2015-03-29 01:59:59.999999999+01:00',
                           '2015-03-29 03:30:00+02:00',
                           '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)

In [478]: dti.tz_localize("Europe/Warsaw", nonexistent=pd.Timedelta(1, unit="H"))
Out[478]:
DatetimeIndex(['2015-03-29 03:30:00+02:00', '2015-03-29 03:30:00+02:00',
               '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)

In [479]: dti.tz_localize("Europe/Warsaw", nonexistent="NaT")
Out[479]:
DatetimeIndex(['NaT', '2015-03-29 03:30:00+02:00',
               '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)
```

Time zone series operations

A *Series* with time zone **naive** values is represented with a dtype of `datetime64[ns]`.

```
In [480]: s_naive = pd.Series(pd.date_range("20130101", periods=3))

In [481]: s_naive
Out[481]:
0   2013-01-01
1   2013-01-02
2   2013-01-03
dtype: datetime64[ns]
```

A *Series* with a time zone **aware** values is represented with a dtype of `datetime64[ns, tz]` where `tz` is the time zone

```
In [482]: s_aware = pd.Series(pd.date_range("20130101", periods=3, tz="US/Eastern"))

In [483]: s_aware
Out[483]:
0   2013-01-01 00:00:00-05:00
1   2013-01-02 00:00:00-05:00
2   2013-01-03 00:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

Both of these *Series* time zone information can be manipulated via the `.dt` accessor, see *the dt accessor section*.

For example, to localize and convert a naive stamp to time zone aware.

```
In [484]: s_naive.dt.tz_localize("UTC").dt.tz_convert("US/Eastern")
Out[484]:
0   2012-12-31 19:00:00-05:00
1   2013-01-01 19:00:00-05:00
2   2013-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

Time zone information can also be manipulated using the `astype` method. This method can localize and convert time zone naive timestamps or convert time zone aware timestamps.

```
# localize and convert a naive time zone
In [485]: s_naive.astype("datetime64[ns, US/Eastern]")
Out[485]:
0   2012-12-31 19:00:00-05:00
1   2013-01-01 19:00:00-05:00
2   2013-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]

# make an aware tz naive
In [486]: s_aware.astype("datetime64[ns]")
Out[486]:
0   2013-01-01 05:00:00
1   2013-01-02 05:00:00
2   2013-01-03 05:00:00
dtype: datetime64[ns]

# convert to a new time zone
In [487]: s_aware.astype("datetime64[ns, CET]")
Out[487]:
```

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```
0   2013-01-01 06:00:00+01:00
1   2013-01-02 06:00:00+01:00
2   2013-01-03 06:00:00+01:00
dtype: datetime64[ns, CET]
```

Note: Using *`Series.to_numpy()`* on a `Series`, returns a NumPy array of the data. NumPy does not currently support time zones (even though it is *printing* in the local time zone!), therefore an object array of Timestamps is returned for time zone aware data:

```
In [488]: s_naive.to_numpy()
Out[488]:
array(['2013-01-01T00:00:00.000000000', '2013-01-02T00:00:00.000000000',
       '2013-01-03T00:00:00.000000000'], dtype='datetime64[ns]')

In [489]: s_aware.to_numpy()
Out[489]:
array([Timestamp('2013-01-01 00:00:00-0500', tz='US/Eastern', freq='D'),
       Timestamp('2013-01-02 00:00:00-0500', tz='US/Eastern', freq='D'),
       Timestamp('2013-01-03 00:00:00-0500', tz='US/Eastern', freq='D')],
      dtype=object)
```

By converting to an object array of Timestamps, it preserves the time zone information. For example, when converting back to a Series:

```
In [490]: pd.Series(s_aware.to_numpy())
Out[490]:
0   2013-01-01 00:00:00-05:00
1   2013-01-02 00:00:00-05:00
2   2013-01-03 00:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

However, if you want an actual NumPy `datetime64[ns]` array (with the values converted to UTC) instead of an array of objects, you can specify the `dtype` argument:

```
In [491]: s_aware.to_numpy(dtype="datetime64[ns]")
Out[491]:
array(['2013-01-01T05:00:00.000000000', '2013-01-02T05:00:00.000000000',
       '2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

2.20 Time deltas

Timedeltas are differences in times, expressed in difference units, e.g. days, hours, minutes, seconds. They can be both positive and negative.

`Timedelta` is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes.

2.20.1 Parsing

You can construct a `Timedelta` scalar through various arguments, including ISO 8601 Duration strings.

```
In [1]: import datetime

# strings
In [2]: pd.Timedelta("1 days")
Out[2]: Timedelta('1 days 00:00:00')

In [3]: pd.Timedelta("1 days 00:00:00")
Out[3]: Timedelta('1 days 00:00:00')

In [4]: pd.Timedelta("1 days 2 hours")
Out[4]: Timedelta('1 days 02:00:00')

In [5]: pd.Timedelta("-1 days 2 min 3us")
Out[5]: Timedelta('-2 days +23:57:59.999997')

# like datetime.timedelta
# note: these MUST be specified as keyword arguments
In [6]: pd.Timedelta(days=1, seconds=1)
Out[6]: Timedelta('1 days 00:00:01')

# integers with a unit
In [7]: pd.Timedelta(1, unit="d")
Out[7]: Timedelta('1 days 00:00:00')

# from a datetime.timedelta/np.timedelta64
In [8]: pd.Timedelta(datetime.timedelta(days=1, seconds=1))
Out[8]: Timedelta('1 days 00:00:01')

In [9]: pd.Timedelta(np.timedelta64(1, "ms"))
Out[9]: Timedelta('0 days 00:00:00.001000')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [10]: pd.Timedelta("-1us")
Out[10]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [11]: pd.Timedelta("nan")
Out[11]: NaT

In [12]: pd.Timedelta("nat")
Out[12]: NaT

# ISO 8601 Duration strings
In [13]: pd.Timedelta("P0DT0H1M0S")
Out[13]: Timedelta('0 days 00:01:00')

In [14]: pd.Timedelta("P0DT0H0M0.000000123S")
Out[14]: Timedelta('0 days 00:00:00.000000123')
```

DateOffsets (`Day`, `Hour`, `Minute`, `Second`, `Milli`, `Micro`, `Nano`) can also be used in construction.

```
In [15]: pd.Timedelta(pd.offsets.Second(2))
Out[15]: Timedelta('0 days 00:00:02')
```

Further, operations among the scalars yield another scalar `Timedelta`.

```
In [16]: pd.Timedelta(pd.offsets.Day(2)) + pd.Timedelta(pd.offsets.Second(2)) + pd.
↪Timedelta(
   ....:     "00:00:00.000123"
   ....: )
   ....:
Out[16]: Timedelta('2 days 00:00:02.000123')
```

to_timedelta

Using the top-level `pd.to_timedelta`, you can convert a scalar, array, list, or Series from a recognized timedelta format / value into a `Timedelta` type. It will construct Series if the input is a Series, a scalar if the input is scalar-like, otherwise it will output a `TimedeltaIndex`.

You can parse a single string to a Timedelta:

```
In [17]: pd.to_timedelta("1 days 06:05:01.00003")
Out[17]: Timedelta('1 days 06:05:01.000030')

In [18]: pd.to_timedelta("15.5us")
Out[18]: Timedelta('0 days 00:00:00.000015500')
```

or a list/array of strings:

```
In [19]: pd.to_timedelta(["1 days 06:05:01.00003", "15.5us", "nan"])
Out[19]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015500', NaT],␣
↪dtype='timedelta64[ns]', freq=None)
```

The `unit` keyword argument specifies the unit of the Timedelta:

```
In [20]: pd.to_timedelta(np.arange(5), unit="s")
Out[20]:
TimedeltaIndex(['0 days 00:00:00', '0 days 00:00:01', '0 days 00:00:02',
                '0 days 00:00:03', '0 days 00:00:04'],
               dtype='timedelta64[ns]', freq=None)

In [21]: pd.to_timedelta(np.arange(5), unit="d")
Out[21]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype=
↪'timedelta64[ns]', freq=None)
```

Timedelta limitations

pandas represents `Timedeltas` in nanosecond resolution using 64 bit integers. As such, the 64 bit integer limits determine the `Timedelta` limits.

```
In [22]: pd.Timedelta.min
Out[22]: Timedelta('-106752 days +00:12:43.145224193')

In [23]: pd.Timedelta.max
Out[23]: Timedelta('106751 days 23:47:16.854775807')
```

2.20.2 Operations

You can operate on Series/DataFrames and construct `timedelta64[ns]` Series through subtraction operations on `datetime64[ns]` Series, or `Timestamps`.

```
In [24]: s = pd.Series(pd.date_range("2012-1-1", periods=3, freq="D"))

In [25]: td = pd.Series([pd.Timedelta(days=i) for i in range(3)])

In [26]: df = pd.DataFrame({"A": s, "B": td})

In [27]: df
Out[27]:
           A      B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [28]: df["C"] = df["A"] + df["B"]

In [29]: df
Out[29]:
           A      B          C
0 2012-01-01 0 days 2012-01-01
1 2012-01-02 1 days 2012-01-03
2 2012-01-03 2 days 2012-01-05

In [30]: df.dtypes
Out[30]:
A     datetime64[ns]
B    timedelta64[ns]
C     datetime64[ns]
dtype: object

In [31]: s - s.max()
Out[31]:
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [32]: s - datetime.datetime(2011, 1, 1, 3, 5)
Out[32]:
0   364 days 20:55:00
1   365 days 20:55:00
2   366 days 20:55:00
dtype: timedelta64[ns]

In [33]: s + datetime.timedelta(minutes=5)
Out[33]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [34]: s + pd.offsets.Minute(5)
Out[34]:
0   2012-01-01 00:05:00
```

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```
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [35]: s + pd.offsets.Minute(5) + pd.offsets.Milli(5)
Out[35]:
0   2012-01-01 00:05:00.005
1   2012-01-02 00:05:00.005
2   2012-01-03 00:05:00.005
dtype: datetime64[ns]
```

Operations with scalars from a `timedelta64[ns]` series:

```
In [36]: y = s - s[0]

In [37]: y
Out[37]:
0   0 days
1   1 days
2   2 days
dtype: timedelta64[ns]
```

Series of timedeltas with `NaT` values are supported:

```
In [38]: y = s - s.shift()

In [39]: y
Out[39]:
0      NaT
1   1 days
2   1 days
dtype: timedelta64[ns]
```

Elements can be set to `NaT` using `np.nan` analogously to datetimes:

```
In [40]: y[1] = np.nan

In [41]: y
Out[41]:
0      NaT
1      NaT
2   1 days
dtype: timedelta64[ns]
```

Operands can also appear in a reversed order (a singular object operated with a Series):

```
In [42]: s.max() - s
Out[42]:
0   2 days
1   1 days
2   0 days
dtype: timedelta64[ns]

In [43]: datetime.datetime(2011, 1, 1, 3, 5) - s
Out[43]:
0   -365 days +03:05:00
```

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```
1   -366 days +03:05:00
2   -367 days +03:05:00
dtype: timedelta64[ns]

In [44]: datetime.timedelta(minutes=5) + s
Out[44]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]
```

`min`, `max` and the corresponding `idxmin`, `idxmax` operations are supported on frames:

```
In [45]: A = s - pd.Timestamp("20120101") - pd.Timedelta("00:05:05")

In [46]: B = s - pd.Series(pd.date_range("2012-1-2", periods=3, freq="D"))

In [47]: df = pd.DataFrame({"A": A, "B": B})

In [48]: df
Out[48]:
                  A       B
0 -1 days +23:54:55 -1 days
1   0 days 23:54:55 -1 days
2   1 days 23:54:55 -1 days

In [49]: df.min()
Out[49]:
A   -1 days +23:54:55
B   -1 days +00:00:00
dtype: timedelta64[ns]

In [50]: df.min(axis=1)
Out[50]:
0   -1 days
1   -1 days
2   -1 days
dtype: timedelta64[ns]

In [51]: df.idxmin()
Out[51]:
A    0
B    0
dtype: int64

In [52]: df.idxmax()
Out[52]:
A    2
B    0
dtype: int64
```

`min`, `max`, `idxmin`, `idxmax` operations are supported on Series as well. A scalar result will be a `Timedelta`.

```
In [53]: df.min().max()
Out[53]: Timedelta('-1 days +23:54:55')

In [54]: df.min(axis=1).min()
```

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```
Out[54]: Timedelta('-1 days +00:00:00')

In [55]: df.min().idxmax()
Out[55]: 'A'

In [56]: df.min(axis=1).idxmin()
Out[56]: 0
```

You can fillna on timedeltas, passing a timedelta to get a particular value.

```
In [57]: y.fillna(pd.Timedelta(0))
Out[57]:
0   0 days
1   0 days
2   1 days
dtype: timedelta64[ns]

In [58]: y.fillna(pd.Timedelta(10, unit="s"))
Out[58]:
0   0 days 00:00:10
1   0 days 00:00:10
2   1 days 00:00:00
dtype: timedelta64[ns]

In [59]: y.fillna(pd.Timedelta("-1 days, 00:00:05"))
Out[59]:
0   -1 days +00:00:05
1   -1 days +00:00:05
2     1 days 00:00:00
dtype: timedelta64[ns]
```

You can also negate, multiply and use `abs` on `Timedeltas`:

```
In [60]: td1 = pd.Timedelta("-1 days 2 hours 3 seconds")

In [61]: td1
Out[61]: Timedelta('-2 days +21:59:57')

In [62]: -1 * td1
Out[62]: Timedelta('1 days 02:00:03')

In [63]: -td1
Out[63]: Timedelta('1 days 02:00:03')

In [64]: abs(td1)
Out[64]: Timedelta('1 days 02:00:03')
```

2.20.3 Reductions

Numeric reduction operation for `timedelta64[ns]` will return `Timedelta` objects. As usual `NaT` are skipped during evaluation.

```
In [65]: y2 = pd.Series(
   ....:     pd.to_timedelta(["-1 days +00:00:05", "nat", "-1 days +00:00:05", "1 days
↪"])
   ....: )
   ....:

In [66]: y2
Out[66]:
0   -1 days +00:00:05
1                 NaT
2   -1 days +00:00:05
3     1 days 00:00:00
dtype: timedelta64[ns]

In [67]: y2.mean()
Out[67]: Timedelta('-1 days +16:00:03.333333334')

In [68]: y2.median()
Out[68]: Timedelta('-1 days +00:00:05')

In [69]: y2.quantile(0.1)
Out[69]: Timedelta('-1 days +00:00:05')

In [70]: y2.sum()
Out[70]: Timedelta('-1 days +00:00:10')
```

2.20.4 Frequency conversion

Timedelta Series, `TimedeltaIndex`, and `Timedelta` scalars can be converted to other 'frequencies' by dividing by another timedelta, or by astyping to a specific timedelta type. These operations yield Series and propagate `NaT` -> `nan`. Note that division by the NumPy scalar is true division, while astyping is equivalent of floor division.

```
In [71]: december = pd.Series(pd.date_range("20121201", periods=4))

In [72]: january = pd.Series(pd.date_range("20130101", periods=4))

In [73]: td = january - december

In [74]: td[2] += datetime.timedelta(minutes=5, seconds=3)

In [75]: td[3] = np.nan

In [76]: td
Out[76]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3                NaT
dtype: timedelta64[ns]

# to days
```

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```
In [77]: td / np.timedelta64(1, "D")
Out[77]:
0    31.000000
1    31.000000
2    31.003507
3          NaN
dtype: float64

In [78]: td.astype("timedelta64[D]")
Out[78]:
0    31.0
1    31.0
2    31.0
3     NaN
dtype: float64

# to seconds
In [79]: td / np.timedelta64(1, "s")
Out[79]:
0    2678400.0
1    2678400.0
2    2678703.0
3          NaN
dtype: float64

In [80]: td.astype("timedelta64[s]")
Out[80]:
0    2678400.0
1    2678400.0
2    2678703.0
3          NaN
dtype: float64

# to months (these are constant months)
In [81]: td / np.timedelta64(1, "M")
Out[81]:
0    1.018501
1    1.018501
2    1.018617
3         NaN
dtype: float64
```

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series yields another `timedelta64[ns]` dtypes Series.

```
In [82]: td * -1
Out[82]:
0   -31 days +00:00:00
1   -31 days +00:00:00
2   -32 days +23:54:57
3                  NaT
dtype: timedelta64[ns]

In [83]: td * pd.Series([1, 2, 3, 4])
Out[83]:
0   31 days 00:00:00
```

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```
1   62 days 00:00:00
2   93 days 00:15:09
3                NaT
dtype: timedelta64[ns]
```

Rounded division (floor-division) of a `timedelta64[ns]` Series by a scalar `Timedelta` gives a series of integers.

```
In [84]: td // pd.Timedelta(days=3, hours=4)
Out[84]:
0    9.0
1    9.0
2    9.0
3    NaN
dtype: float64

In [85]: pd.Timedelta(days=3, hours=4) // td
Out[85]:
0    0.0
1    0.0
2    0.0
3    NaN
dtype: float64
```

The mod (%) and divmod operations are defined for `Timedelta` when operating with another timedelta-like or with a numeric argument.

```
In [86]: pd.Timedelta(hours=37) % datetime.timedelta(hours=2)
Out[86]: Timedelta('0 days 01:00:00')

# divmod against a timedelta-like returns a pair (int, Timedelta)
In [87]: divmod(datetime.timedelta(hours=2), pd.Timedelta(minutes=11))
Out[87]: (10, Timedelta('0 days 00:10:00'))

# divmod against a numeric returns a pair (Timedelta, Timedelta)
In [88]: divmod(pd.Timedelta(hours=25), 86400000000000)
Out[88]: (Timedelta('0 days 00:00:00.000000001'), Timedelta('0 days 01:00:00'))
```

2.20.5 Attributes

You can access various components of the `Timedelta` or `TimedeltaIndex` directly using the attributes `days,seconds,microseconds,nanoseconds`. These are identical to the values returned by `datetime.timedelta`, in that, for example, the `.seconds` attribute represents the number of seconds >= 0 and < 1 day. These are signed according to whether the `Timedelta` is signed.

These operations can also be directly accessed via the `.dt` property of the `Series` as well.

Note: Note that the attributes are NOT the displayed values of the `Timedelta`. Use `.components` to retrieve the displayed values.

For a `Series`:

```
In [89]: td.dt.days
Out[89]:
```

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```
0    31.0
1    31.0
2    31.0
3     NaN
dtype: float64

In [90]: td.dt.seconds
Out[90]:
0      0.0
1      0.0
2    303.0
3      NaN
dtype: float64
```

You can access the value of the fields for a scalar `Timedelta` directly.

```
In [91]: tds = pd.Timedelta("31 days 5 min 3 sec")

In [92]: tds.days
Out[92]: 31

In [93]: tds.seconds
Out[93]: 303

In [94]: (-tds).seconds
Out[94]: 86097
```

You can use the `.components` property to access a reduced form of the timedelta. This returns a `DataFrame` indexed similarly to the `Series`. These are the *displayed* values of the `Timedelta`.

```
In [95]: td.dt.components
Out[95]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0  31.0    0.0      0.0      0.0           0.0           0.0          0.0
1  31.0    0.0      0.0      0.0           0.0           0.0          0.0
2  31.0    0.0      5.0      3.0           0.0           0.0          0.0
3   NaN    NaN      NaN      NaN           NaN           NaN          NaN

In [96]: td.dt.components.seconds
Out[96]:
0    0.0
1    0.0
2    3.0
3    NaN
Name: seconds, dtype: float64
```

You can convert a `Timedelta` to an ISO 8601 Duration string with the `.isoformat` method

```
In [97]: pd.Timedelta(
   ....:     days=6, minutes=50, seconds=3, milliseconds=10, microseconds=10,␣
↪nanoseconds=12
   ....: ).isoformat()
   ....:
Out[97]: 'P6DT0H50M3.010010012S'
```

2.20.6 TimedeltaIndex

To generate an index with time delta, you can use either the *TimedeltaIndex* or the *timedelta_range()* constructor.

Using `TimedeltaIndex` you can pass string-like, `Timedelta`, `timedelta`, or `np.timedelta64` objects. Passing `np.nan/pd.NaT/nat` will represent missing values.

```
In [98]: pd.TimedeltaIndex(
   ....:     [
   ....:         "1 days",
   ....:         "1 days, 00:00:05",
   ....:         np.timedelta64(2, "D"),
   ....:         datetime.timedelta(days=2, seconds=2),
   ....:     ]
   ....: )
   ....:
Out[98]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00',
                '2 days 00:00:02'],
               dtype='timedelta64[ns]', freq=None)
```

The string 'infer' can be passed in order to set the frequency of the index as the inferred frequency upon creation:

```
In [99]: pd.TimedeltaIndex(["0 days", "10 days", "20 days"], freq="infer")
Out[99]: TimedeltaIndex(['0 days', '10 days', '20 days'], dtype='timedelta64[ns]',␣
↪freq='10D')
```

Generating ranges of time deltas

Similar to *date_range()*, you can construct regular ranges of a `TimedeltaIndex` using *timedelta_range()*. The default frequency for `timedelta_range` is calendar day:

```
In [100]: pd.timedelta_range(start="1 days", periods=5)
Out[100]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype=
↪'timedelta64[ns]', freq='D')
```

Various combinations of `start`, `end`, and `periods` can be used with `timedelta_range`:

```
In [101]: pd.timedelta_range(start="1 days", end="5 days")
Out[101]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype=
↪'timedelta64[ns]', freq='D')

In [102]: pd.timedelta_range(end="10 days", periods=4)
Out[102]: TimedeltaIndex(['7 days', '8 days', '9 days', '10 days'], dtype=
↪'timedelta64[ns]', freq='D')
```

The `freq` parameter can passed a variety of *frequency aliases*:

```
In [103]: pd.timedelta_range(start="1 days", end="2 days", freq="30T")
Out[103]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
                '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
                '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
                '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
                '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
```

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```
                '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
                '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
                '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
                '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
                '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
                '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
                '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
                '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
                '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
                '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
                '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
                '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='30T')

In [104]: pd.timedelta_range(start="1 days", periods=5, freq="2D5H")
Out[104]:
TimedeltaIndex(['1 days 00:00:00', '3 days 05:00:00', '5 days 10:00:00',
                '7 days 15:00:00', '9 days 20:00:00'],
               dtype='timedelta64[ns]', freq='53H')
```

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced timedeltas from `start` to `end` inclusively, with `periods` number of elements in the resulting `TimedeltaIndex`:

```
In [105]: pd.timedelta_range("0 days", "4 days", periods=5)
Out[105]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype=
↪'timedelta64[ns]', freq=None)

In [106]: pd.timedelta_range("0 days", "4 days", periods=10)
Out[106]:
TimedeltaIndex(['0 days 00:00:00', '0 days 10:40:00', '0 days 21:20:00',
                '1 days 08:00:00', '1 days 18:40:00', '2 days 05:20:00',
                '2 days 16:00:00', '3 days 02:40:00', '3 days 13:20:00',
                '4 days 00:00:00'],
               dtype='timedelta64[ns]', freq=None)
```

Using the TimedeltaIndex

Similarly to other of the datetime-like indices, `DatetimeIndex` and `PeriodIndex`, you can use `TimedeltaIndex` as the index of pandas objects.

```
In [107]: s = pd.Series(
   .....:     np.arange(100),
   .....:     index=pd.timedelta_range("1 days", periods=100, freq="h"),
   .....: )
   .....:

In [108]: s
Out[108]:
1 days 00:00:00     0
1 days 01:00:00     1
1 days 02:00:00     2
1 days 03:00:00     3
1 days 04:00:00     4
                   ..
4 days 23:00:00    95
```

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```
5 days 00:00:00    96
5 days 01:00:00    97
5 days 02:00:00    98
5 days 03:00:00    99
Freq: H, Length: 100, dtype: int64
```

Selections work similarly, with coercion on string-likes and slices:

```
In [109]: s["1 day":"2 day"]
Out[109]:
1 days 00:00:00     0
1 days 01:00:00     1
1 days 02:00:00     2
1 days 03:00:00     3
1 days 04:00:00     4
                   ..
2 days 19:00:00    43
2 days 20:00:00    44
2 days 21:00:00    45
2 days 22:00:00    46
2 days 23:00:00    47
Freq: H, Length: 48, dtype: int64

In [110]: s["1 day 01:00:00"]
Out[110]: 1

In [111]: s[pd.Timedelta("1 day 1h")]
Out[111]: 1
```

Furthermore you can use partial string selection and the range will be inferred:

```
In [112]: s["1 day":"1 day 5 hours"]
Out[112]:
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
1 days 05:00:00    5
Freq: H, dtype: int64
```

Operations

Finally, the combination of `TimedeltaIndex` with `DatetimeIndex` allow certain combination operations that are NaT preserving:

```
In [113]: tdi = pd.TimedeltaIndex(["1 days", pd.NaT, "2 days"])

In [114]: tdi.to_list()
Out[114]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [115]: dti = pd.date_range("20130101", periods=3)

In [116]: dti.to_list()
Out[116]:
```

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```
[Timestamp('2013-01-01 00:00:00', freq='D'),
 Timestamp('2013-01-02 00:00:00', freq='D'),
 Timestamp('2013-01-03 00:00:00', freq='D')]

In [117]: (dti + tdi).to_list()
Out[117]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [118]: (dti - tdi).to_list()
Out[118]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

Conversions

Similarly to frequency conversion on a `Series` above, you can convert these indices to yield another Index.

```
In [119]: tdi / np.timedelta64(1, "s")
Out[119]: Float64Index([86400.0, nan, 172800.0], dtype='float64')

In [120]: tdi.astype("timedelta64[s]")
Out[120]: Float64Index([86400.0, nan, 172800.0], dtype='float64')
```

Scalars type ops work as well. These can potentially return a *different* type of index.

```
# adding or timedelta and date -> datelike
In [121]: tdi + pd.Timestamp("20130101")
Out[121]: DatetimeIndex(['2013-01-02', 'NaT', '2013-01-03'], dtype='datetime64[ns]',␣
↪freq=None)

# subtraction of a date and a timedelta -> datelike
# note that trying to subtract a date from a Timedelta will raise an exception
In [122]: (pd.Timestamp("20130101") - tdi).to_list()
Out[122]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2012-12-30 00:00:00')]

# timedelta + timedelta -> timedelta
In [123]: tdi + pd.Timedelta("10 days")
Out[123]: TimedeltaIndex(['11 days', NaT, '12 days'], dtype='timedelta64[ns]',␣
↪freq=None)

# division can result in a Timedelta if the divisor is an integer
In [124]: tdi / 2
Out[124]: TimedeltaIndex(['0 days 12:00:00', NaT, '1 days 00:00:00'], dtype=
↪'timedelta64[ns]', freq=None)

# or a Float64Index if the divisor is a Timedelta
In [125]: tdi / tdi[0]
Out[125]: Float64Index([1.0, nan, 2.0], dtype='float64')
```

2.20.7 Resampling

Similar to *timeseries resampling*, we can resample with a `TimedeltaIndex`.

```
In [126]: s.resample("D").mean()
Out[126]:
1 days    11.5
2 days    35.5
3 days    59.5
4 days    83.5
5 days    97.5
Freq: D, dtype: float64
```

2.21 Styling

This document is written as a Jupyter Notebook, and can be viewed or downloaded here.

You can apply **conditional formatting**, the visual styling of a DataFrame depending on the data within, by using the `DataFrame.style` property. This is a property that returns a `Styler` object, which has useful methods for formatting and displaying DataFrames.

The styling is accomplished using CSS. You write "style functions" that take scalars, `DataFrames` or `Series`, and return *like-indexed* DataFrames or Series with CSS `"attribute: value"` pairs for the values. These functions can be incrementally passed to the `Styler` which collects the styles before rendering.

2.21.1 Building styles

Pass your style functions into one of the following methods:

- `Styler.applymap`: elementwise
- `Styler.apply`: column-/row-/table-wise

Both of those methods take a function (and some other keyword arguments) and applies your function to the DataFrame in a certain way. `Styler.applymap` works through the DataFrame elementwise. `Styler.apply` passes each column or row into your DataFrame one-at-a-time or the entire table at once, depending on the `axis` keyword argument. For columnwise use `axis=0`, rowwise use `axis=1`, and for the entire table at once use `axis=None`.

For `Styler.applymap` your function should take a scalar and return a single string with the CSS attribute-value pair.

For `Styler.apply` your function should take a Series or DataFrame (depending on the axis parameter), and return a Series or DataFrame with an identical shape where each value is a string with a CSS attribute-value pair.

Let's see some examples.

[2]:
```
import pandas as pd
import numpy as np

np.random.seed(24)
df = pd.DataFrame({'A': np.linspace(1, 10, 10)})
df = pd.concat([df, pd.DataFrame(np.random.randn(10, 4), columns=list('BCDE'))],
               axis=1)
df.iloc[3, 3] = np.nan
df.iloc[0, 2] = np.nan
```

Here's a boring example of rendering a DataFrame, without any (visible) styles:

[3]:
```
df.style
```

[3]:
```
<pandas.io.formats.style.Styler at 0x7f722316a2e0>
```

Note: The `DataFrame.style` attribute is a property that returns a `Styler` object. `Styler` has a `_repr_html_` method defined on it so they are rendered automatically. If you want the actual HTML back for further processing or for writing to file call the `.render()` method which returns a string.

The above output looks very similar to the standard DataFrame HTML representation. But we've done some work behind the scenes to attach CSS classes to each cell. We can view these by calling the `.render` method.

[4]:
```
df.style.highlight_null().render().split('\n')[:10]
```

[4]:
```
['<style  type="text/css" >',
 '#T_787d1_row0_col2,#T_787d1_row3_col3{',
 '            background-color:  red;',
 '        }</style><table id="T_787d1_" ><thead>    <tr>        <th class="blank␣
↪level0" ></th>        <th class="col_heading level0 col0" >A</th>        <th class=
↪"col_heading level0 col1" >B</th>        <th class="col_heading level0 col2" >C</th>
↪        <th class="col_heading level0 col3" >D</th>        <th class="col_heading␣
↪level0 col4" >E</th>    </tr></thead><tbody>',
 '                <tr>',
 '                        <th id="T_787d1_level0_row0" class="row_heading level0 row0
↪" >0</th>',
 '                        <td id="T_787d1_row0_col0" class="data row0 col0" >1.000000
↪</td>',
 '                        <td id="T_787d1_row0_col1" class="data row0 col1" >1.329212
↪</td>',
 '                        <td id="T_787d1_row0_col2" class="data row0 col2" >nan</td>
↪',
 '                        <td id="T_787d1_row0_col3" class="data row0 col3" >-0.316280
↪</td>']
```

The `row0_col2` is the identifier for that particular cell. We've also prepended each row/column identifier with a UUID unique to each DataFrame so that the style from one doesn't collide with the styling from another within the same notebook or page (you can set the `uuid` if you'd like to tie together the styling of two DataFrames).

When writing style functions, you take care of producing the CSS attribute / value pairs you want. Pandas matches those up with the CSS classes that identify each cell.

Let's write a simple style function that will color negative numbers red and positive numbers black.

[5]:
```
def color_negative_red(val):
    """
    Takes a scalar and returns a string with
    the css property `'color: red'` for negative
    strings, black otherwise.
    """
    color = 'red' if val < 0 else 'black'
    return 'color: %s' % color
```

In this case, the cell's style depends only on its own value. That means we should use the `Styler.applymap` method which works elementwise.

[6]:
```
s = df.style.applymap(color_negative_red)
s
```

[6]:
```
<pandas.io.formats.style.Styler at 0x7f72bc61c070>
```

Notice the similarity with the standard `df.applymap`, which operates on DataFrames elementwise. We want you to be able to reuse your existing knowledge of how to interact with DataFrames.

Notice also that our function returned a string containing the CSS attribute and value, separated by a colon just like in a `<style>` tag. This will be a common theme.

Finally, the input shapes matched. `Styler.applymap` calls the function on each scalar input, and the function returns a scalar output.

Now suppose you wanted to highlight the maximum value in each column. We can't use `.applymap` anymore since that operated elementwise. Instead, we'll turn to `.apply` which operates columnwise (or rowwise using the `axis` keyword). Later on we'll see that something like `highlight_max` is already defined on `Styler` so you wouldn't need to write this yourself.

[7]:
```
def highlight_max(s):
    '''
    highlight the maximum in a Series yellow.
    '''
    is_max = s == s.max()
    return ['background-color: yellow' if v else '' for v in is_max]
```

[8]:
```
df.style.apply(highlight_max)
```

[8]:
```
<pandas.io.formats.style.Styler at 0x7f72a3cadf70>
```

In this case the input is a `Series`, one column at a time. Notice that the output shape of `highlight_max` matches the input shape, an array with `len(s)` items.

We encourage you to use method chains to build up a style piecewise, before finally rending at the end of the chain.

[9]:
```
df.style.\
    applymap(color_negative_red).\
    apply(highlight_max)
```

[9]:
```
<pandas.io.formats.style.Styler at 0x7f72a3ba7c70>
```

Above we used `Styler.apply` to pass in each column one at a time.

Debugging Tip: If you're having trouble writing your style function, try just passing it into DataFrame.apply. Internally, Styler.apply uses DataFrame.apply so the result should be the same.

What if you wanted to highlight just the maximum value in the entire table? Use `.apply(function, axis=None)` to indicate that your function wants the entire table, not one column or row at a time. Let's try that next.

We'll rewrite our `highlight-max` to handle either Series (from `.apply(axis=0 or 1)`) or DataFrames (from `.apply(axis=None)`). We'll also allow the color to be adjustable, to demonstrate that `.apply`, and `.applymap` pass along keyword arguments.

[10]:
```
def highlight_max(data, color='yellow'):
    '''
    highlight the maximum in a Series or DataFrame
    '''
    attr = 'background-color: {}'.format(color)
    if data.ndim == 1:  # Series from .apply(axis=0) or axis=1
        is_max = data == data.max()
        return [attr if v else '' for v in is_max]
    else:  # from .apply(axis=None)
        is_max = data == data.max().max()
```

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```
        return pd.DataFrame(np.where(is_max, attr, ''),
                            index=data.index, columns=data.columns)
```

When using `Styler.apply(func, axis=None)`, the function must return a DataFrame with the same index and column labels.

[11]:
```
df.style.apply(highlight_max, color='darkorange', axis=None)
```

[11]:
```
<pandas.io.formats.style.Styler at 0x7f72a3ba77f0>
```

Building Styles Summary

Style functions should return strings with one or more CSS `attribute: value` delimited by semicolons. Use

- `Styler.applymap(func)` for elementwise styles
- `Styler.apply(func, axis=0)` for columnwise styles
- `Styler.apply(func, axis=1)` for rowwise styles
- `Styler.apply(func, axis=None)` for tablewise styles

And crucially the input and output shapes of `func` must match. If `x` is the input then `func(x).shape == x.shape`.

2.21.2 Finer control: slicing

Both `Styler.apply`, and `Styler.applymap` accept a `subset` keyword. This allows you to apply styles to specific rows or columns, without having to code that logic into your `style` function.

The value passed to `subset` behaves similar to slicing a DataFrame.

- A scalar is treated as a column label
- A list (or series or numpy array)
- A tuple is treated as `(row_indexer, column_indexer)`

Consider using `pd.IndexSlice` to construct the tuple for the last one.

[12]:
```
df.style.apply(highlight_max, subset=['B', 'C', 'D'])
```

[12]:
```
<pandas.io.formats.style.Styler at 0x7f72a3bb5760>
```

For row and column slicing, any valid indexer to `.loc` will work.

[13]:
```
df.style.applymap(color_negative_red,
                  subset=pd.IndexSlice[2:5, ['B', 'D']])
```

[13]:
```
<pandas.io.formats.style.Styler at 0x7f72a3bb53d0>
```

Only label-based slicing is supported right now, not positional.

If your style function uses a `subset` or `axis` keyword argument, consider wrapping your function in a `functools.partial`, partialing out that keyword.

```
my_func2 = functools.partial(my_func, subset=42)
```

2.21.3 Finer Control: Display Values

We distinguish the *display* value from the *actual* value in `Styler`. To control the display value, the text is printed in each cell, use `Styler.format`. Cells can be formatted according to a format spec string or a callable that takes a single value and returns a string.

[14]:
```
df.style.format("{:.2%}")
```

[14]:
```
<pandas.io.formats.style.Styler at 0x7f72a3bb58b0>
```

Use a dictionary to format specific columns.

[15]:
```
df.style.format({'B': "{:0<4.0f}", 'D': '{:+.2f}'})
```

[15]:
```
<pandas.io.formats.style.Styler at 0x7f72a3bb5640>
```

Or pass in a callable (or dictionary of callables) for more flexible handling.

[16]:
```
df.style.format({"B": lambda x: "±{:.2f}".format(abs(x))})
```

[16]:
```
<pandas.io.formats.style.Styler at 0x7f72a3bb5a60>
```

You can format the text displayed for missing values by `na_rep`.

[17]:
```
df.style.format("{:.2%}", na_rep="-")
```

[17]:
```
<pandas.io.formats.style.Styler at 0x7f72a3ba7820>
```

These formatting techniques can be used in combination with styling.

[18]:
```
df.style.highlight_max().format(None, na_rep="-")
```

[18]:
```
<pandas.io.formats.style.Styler at 0x7f72bc5fae50>
```

2.21.4 Builtin styles

Finally, we expect certain styling functions to be common enough that we've included a few "built-in" to the `Styler`, so you don't have to write them yourself.

[19]:
```
df.style.highlight_null(null_color='red')
```

[19]:
```
<pandas.io.formats.style.Styler at 0x7f72a3bb5df0>
```

You can create "heatmaps" with the `background_gradient` method. These require matplotlib, and we'll use Seaborn to get a nice colormap.

[20]:
```
import seaborn as sns

cm = sns.light_palette("green", as_cmap=True)

s = df.style.background_gradient(cmap=cm)
s
```

[20]:
```
<pandas.io.formats.style.Styler at 0x7f72a3ea2e50>
```

`Styler.background_gradient` takes the keyword arguments `low` and `high`. Roughly speaking these extend the range of your data by `low` and `high` percent so that when we convert the colors, the colormap's entire range isn't used. This is useful so that you can actually read the text still.

[21]:
```
# Uses the full color range
df.loc[:4].style.background_gradient(cmap='viridis')
```

[21]:
```
<pandas.io.formats.style.Styler at 0x7f72a3bb56d0>
```

[22]:
```
# Compress the color range
(df.loc[:4]
    .style
    .background_gradient(cmap='viridis', low=.5, high=0)
    .highlight_null('red'))
```

[22]:
```
<pandas.io.formats.style.Styler at 0x7f72677f2340>
```

There's also `.highlight_min` and `.highlight_max`.

[23]:
```
df.style.highlight_max(axis=0)
```

[23]:
```
<pandas.io.formats.style.Styler at 0x7f72677f25e0>
```

Use `Styler.set_properties` when the style doesn't actually depend on the values.

[24]:
```
df.style.set_properties(**{'background-color': 'black',
                           'color': 'lawngreen',
                           'border-color': 'white'})
```

[24]:
```
<pandas.io.formats.style.Styler at 0x7f72677f2460>
```

Bar charts

You can include "bar charts" in your DataFrame.

[25]:
```
df.style.bar(subset=['A', 'B'], color='#d65f5f')
```

[25]:
```
<pandas.io.formats.style.Styler at 0x7f72677e2b80>
```

New in version 0.20.0 is the ability to customize further the bar chart: You can now have the `df.style.bar` be centered on zero or midpoint value (in addition to the already existing way of having the min value at the left side of the cell), and you can pass a list of `[color_negative, color_positive]`.

Here's how you can change the above with the new `align='mid'` option:

[26]:
```
df.style.bar(subset=['A', 'B'], align='mid', color=['#d65f5f', '#5fba7d'])
```

[26]:
```
<pandas.io.formats.style.Styler at 0x7f726780ec10>
```

The following example aims to give a highlight of the behavior of the new align options:

[27]:
```
import pandas as pd
from IPython.display import HTML

# Test series
test1 = pd.Series([-100,-60,-30,-20], name='All Negative')
test2 = pd.Series([10,20,50,100], name='All Positive')
test3 = pd.Series([-10,-5,0,90], name='Both Pos and Neg')

head = """
<table>
    <thead>
```

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```
        <th>Align</th>
        <th>All Negative</th>
        <th>All Positive</th>
        <th>Both Neg and Pos</th>
    </thead>
    </tbody>

"""

aligns = ['left','zero','mid']
for align in aligns:
    row = "<tr><th>{}</th>".format(align)
    for series in [test1,test2,test3]:
        s = series.copy()
        s.name=''
        row += "<td>{}</td>".format(s.to_frame().style.bar(align=align,
                                                           color=['#d65f5f', '#5fba7d
↪'],
                                                           width=100).render())
↪#testn['width']
    row += '</tr>'
    head += row

head+= """
</tbody>
</table>"""


HTML(head)
```

[27]:
```
<IPython.core.display.HTML object>
```

2.21.5 Sharing styles

Say you have a lovely style built up for a DataFrame, and now you want to apply the same style to a second DataFrame. Export the style with `df1.style.export`, and import it on the second DataFrame with `df1.style.set`

[28]:
```
df2 = -df
style1 = df.style.applymap(color_negative_red)
style1
```

[28]:
```
<pandas.io.formats.style.Styler at 0x7f725f77efa0>
```

[29]:
```
style2 = df2.style
style2.use(style1.export())
style2
```

[29]:
```
<pandas.io.formats.style.Styler at 0x7f725f77ea30>
```

Notice that you're able to share the styles even though they're data aware. The styles are re-evaluated on the new DataFrame they've been `used` upon.

2.21.6 Other Options

You've seen a few methods for data-driven styling. `Styler` also provides a few other options for styles that don't depend on the data.

- precision
- captions
- table-wide styles
- missing values representation
- hiding the index or columns

Each of these can be specified in two ways:

- A keyword argument to `Styler.__init__`
- A call to one of the `.set_` or `.hide_` methods, e.g. `.set_caption` or `.hide_columns`

The best method to use depends on the context. Use the `Styler` constructor when building many styled DataFrames that should all share the same properties. For interactive use, the `.set_` and `.hide_` methods are more convenient.

Precision

You can control the precision of floats using pandas' regular `display.precision` option.

[30]:
```
with pd.option_context('display.precision', 2):
    html = (df.style
              .applymap(color_negative_red)
              .apply(highlight_max))
html
```

[30]:
```
<pandas.io.formats.style.Styler at 0x7f72677f2f70>
```

Or through a `set_precision` method.

[31]:
```
df.style\
  .applymap(color_negative_red)\
  .apply(highlight_max)\
  .set_precision(2)
```

[31]:
```
<pandas.io.formats.style.Styler at 0x7f725f789400>
```

Setting the precision only affects the printed number; the full-precision values are always passed to your style functions. You can always use `df.round(2).style` if you'd prefer to round from the start.

Captions

Regular table captions can be added in a few ways.

[32]:
```
df.style.set_caption('Colormaps, with a caption.')\
    .background_gradient(cmap=cm)
```

[32]:
```
<pandas.io.formats.style.Styler at 0x7f72677f2850>
```

Table styles

The next option you have are "table styles". These are styles that apply to the table as a whole, but don't look at the data. Certain stylings, including pseudo-selectors like `:hover` can only be used this way. These can also be used to set specific row or column based class selectors, as will be shown.

[33]:
```
from IPython.display import HTML

def hover(hover_color="#ffff99"):
    return dict(selector="tr:hover",
                props=[("background-color", "%s" % hover_color)])

styles = [
    hover(),
    dict(selector="th", props=[("font-size", "150%"),
                               ("text-align", "center")]),
    dict(selector="caption", props=[("caption-side", "bottom")])
]
html = (df.style.set_table_styles(styles)
          .set_caption("Hover to highlight."))
html
```

[33]:
```
<pandas.io.formats.style.Styler at 0x7f726780e0a0>
```

`table_styles` should be a list of dictionaries. Each dictionary should have the `selector` and `props` keys. The value for `selector` should be a valid CSS selector. Recall that all the styles are already attached to an `id`, unique to each `Styler`. This selector is in addition to that `id`. The value for `props` should be a list of tuples of `('attribute', 'value')`.

`table_styles` are extremely flexible, but not as fun to type out by hand. We hope to collect some useful ones either in pandas, or preferable in a new package that *builds on top* the tools here.

`table_styles` can be used to add column and row based class descriptors. For large tables this can increase performance by avoiding repetitive individual css for each cell, and it can also simplify style construction in some cases. If `table_styles` is given as a dictionary each key should be a specified column or index value and this will map to specific class CSS selectors of the given column or row.

Note that `Styler.set_table_styles` will overwrite existing styles but can be chained by setting the `overwrite` argument to `False`.

[34]:
```
html = html.set_table_styles({
    'B': [dict(selector='', props=[('color', 'green')])],
    'C': [dict(selector='td', props=[('color', 'red')])],
    }, overwrite=False)
html
```

[34]:
```
<pandas.io.formats.style.Styler at 0x7f726780e0a0>
```

Missing values

You can control the default missing values representation for the entire table through `set_na_rep` method.

[35]:
```
(df.style
   .set_na_rep("FAIL")
   .format(None, na_rep="PASS", subset=["D"])
   .highlight_null("yellow"))
```

[35]:
```
<pandas.io.formats.style.Styler at 0x7f725f78f9a0>
```

Hiding the Index or Columns

The index can be hidden from rendering by calling `Styler.hide_index`. Columns can be hidden from rendering by calling `Styler.hide_columns` and passing in the name of a column, or a slice of columns.

[36]:
```
df.style.hide_index()
```

[36]:
```
<pandas.io.formats.style.Styler at 0x7f72677e28b0>
```

[37]:
```
df.style.hide_columns(['C','D'])
```

[37]:
```
<pandas.io.formats.style.Styler at 0x7f72677e2eb0>
```

CSS classes

Certain CSS classes are attached to cells.

- Index and Column names include `index_name` and `level<k>` where `k` is its level in a MultiIndex
- Index label cells include
  - `row_heading`
  - `row<n>` where `n` is the numeric position of the row
  - `level<k>` where `k` is the level in a MultiIndex
- Column label cells include
  - `col_heading`
  - `col<n>` where `n` is the numeric position of the column
  - `level<k>` where `k` is the level in a MultiIndex
- Blank cells include `blank`
- Data cells include `data`

Limitations

- DataFrame only (use Series.to_frame().style)
- The index and columns must be unique
- No large repr, and performance isn't great; this is intended for summary DataFrames
- You can only style the *values*, not the index or columns (except with table_styles above)
- You can only apply styles, you can't insert new HTML entities

Some of these will be addressed in the future. Performance can suffer when adding styles to each cell in a large DataFrame. It is recommended to apply table or column based styles where possible to limit overall HTML length, as well as setting a shorter UUID to avoid unnecessary repeated data transmission.

Terms

- Style function: a function that's passed into Styler.apply or Styler.applymap and returns values like 'css attribute: value'
- Builtin style functions: style functions that are methods on Styler
- table style: a dictionary with the two keys selector and props. selector is the CSS selector that props will apply to. props is a list of (attribute, value) tuples. A list of table styles passed into Styler.

2.21.7 Fun stuff

Here are a few interesting examples.

Styler interacts pretty well with widgets. If you're viewing this online instead of running the notebook yourself, you're missing out on interactively adjusting the color palette.

[38]:
```
from IPython.html import widgets
@widgets.interact
def f(h_neg=(0, 359, 1), h_pos=(0, 359), s=(0., 99.9), l=(0., 99.9)):
    return df.style.background_gradient(
        cmap=sns.palettes.diverging_palette(h_neg=h_neg, h_pos=h_pos, s=s, l=l,
                                            as_cmap=True)
    )
```

```
/opt/conda/envs/pandas/lib/python3.8/site-packages/IPython/html.py:12: ShimWarning:␣
↪The `IPython.html` package has been deprecated since IPython 4.0. You should import␣
↪from `notebook` instead. `IPython.html.widgets` has moved to `ipywidgets`.
  warn("The `IPython.html` package has been deprecated since IPython 4.0. "
```

```
interactive(children=(IntSlider(value=179, description='h_neg', max=359),␣
↪IntSlider(value=179, description='h_...
```

[39]:
```
def magnify():
    return [dict(selector="th",
                 props=[("font-size", "4pt")]),
            dict(selector="td",
                 props=[('padding', "0em 0em")]),
            dict(selector="th:hover",
                 props=[("font-size", "12pt")]),
            dict(selector="tr:hover td:hover",
                 props=[('max-width', '200px'),
```

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```
                           ('font-size', '12pt')])
]
```

[40]:
```
np.random.seed(25)
cmap = cmap=sns.diverging_palette(5, 250, as_cmap=True)
bigdf = pd.DataFrame(np.random.randn(20, 25)).cumsum()

bigdf.style.background_gradient(cmap, axis=1)\
    .set_properties(**{'max-width': '80px', 'font-size': '1pt'})\
    .set_caption("Hover to magnify")\
    .set_precision(2)\
    .set_table_styles(magnify())
```

[40]:
```
<pandas.io.formats.style.Styler at 0x7f7224011ca0>
```

2.21.8 Export to Excel

New in version 0.20.0

Experimental: This is a new feature and still under development. We'll be adding features and possibly making breaking changes in future releases. We'd love to hear your feedback.

Some support is available for exporting styled `DataFrames` to Excel worksheets using the `OpenPyXL` or `XlsxWriter` engines. CSS2.2 properties handled include:

- `background-color`
- `border-style`, `border-width`, `border-color` and their {`top`, `right`, `bottom`, `left` variants}
- `color`
- `font-family`
- `font-style`
- `font-weight`
- `text-align`
- `text-decoration`
- `vertical-align`
- `white-space: nowrap`
- Only CSS2 named colors and hex colors of the form `#rgb` or `#rrggbb` are currently supported.
- The following pseudo CSS properties are also available to set excel specific style properties:
  - `number-format`

[41]:
```
df.style.\
    applymap(color_negative_red).\
    apply(highlight_max).\
    to_excel('styled.xlsx', engine='openpyxl')
```

A screenshot of the output:

	A	B	C	D	E	F
1		A	B	C	D	E
2	0	1	1.329212		-0.31628	-0.99081
3	1	2	-1.070816	-1.438713	0.564417	0.295722
4	2	3	-1.626404	0.219565	0.678805	1.889273
5	3	4	0.961538	0.104011	-0.481165	0.850229
6	4	5	1.453425	1.057737	0.165562	0.515018
7	5	6	-1.336936	0.562861	1.392855	-0.063328
8	6	7	0.121668	1.207603	-0.00204	1.627796
9	7	8	0.354493	1.037528	-0.385684	0.519818
10	8	9	1.686583	-1.325963	1.428984	-2.089354
11	9	10	-0.12982	0.631523	-0.586538	0.29072

2.21.9 Extensibility

The core of pandas is, and will remain, its "high-performance, easy-to-use data structures". With that in mind, we hope that `DataFrame.style` accomplishes two goals

- Provide an API that is pleasing to use interactively and is "good enough" for many tasks
- Provide the foundations for dedicated libraries to build on

If you build a great library on top of this, let us know and we'll link to it.

Subclassing

If the default template doesn't quite suit your needs, you can subclass Styler and extend or override the template. We'll show an example of extending the default template to insert a custom header before each table.

[42]:
```
from jinja2 import Environment, ChoiceLoader, FileSystemLoader
from IPython.display import HTML
from pandas.io.formats.style import Styler
```

We'll use the following template:

[43]:
```
with open("templates/myhtml.tpl") as f:
    print(f.read())
```

```
{% extends "html.tpl" %}
{% block table %}
<h1>{{ table_title|default("My Table") }}</h1>
{{ super() }}
{% endblock table %}
```

Now that we've created a template, we need to set up a subclass of `Styler` that knows about it.

[44]:
```
class MyStyler(Styler):
    env = Environment(
        loader=ChoiceLoader([
            FileSystemLoader("templates"),  # contains ours
            Styler.loader,  # the default
```

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```
        ])
    )
    template = env.get_template("myhtml.tpl")
```

Notice that we include the original loader in our environment's loader. That's because we extend the original template, so the Jinja environment needs to be able to find it.

Now we can use that custom styler. It's `__init__` takes a DataFrame.

[45]:
```
MyStyler(df)
```

[45]:
```
<__main__.MyStyler at 0x7f721a0216a0>
```

Our custom template accepts a `table_title` keyword. We can provide the value in the `.render` method.

[46]:
```
HTML(MyStyler(df).render(table_title="Extending Example"))
```

[46]:
```
<IPython.core.display.HTML object>
```

For convenience, we provide the `Styler.from_custom_template` method that does the same as the custom subclass.

[47]:
```
EasyStyler = Styler.from_custom_template("templates", "myhtml.tpl")
EasyStyler(df)
```

[47]:
```
<pandas.io.formats.style.Styler.from_custom_template.<locals>.MyStyler at␣
↪0x7f721a08f880>
```

Here's the template structure:

[48]:
```
with open("templates/template_structure.html") as f:
    structure = f.read()

HTML(structure)
```

[48]:
```
<IPython.core.display.HTML object>
```

See the template in the GitHub repo for more details.

2.22 Options and settings

2.22.1 Overview

pandas has an options system that lets you customize some aspects of its behaviour, display-related options being those the user is most likely to adjust.

Options have a full "dotted-style", case-insensitive name (e.g. `display.max_rows`). You can get/set options directly as attributes of the top-level `options` attribute:

```
In [1]: import pandas as pd

In [2]: pd.options.display.max_rows
Out[2]: 15

In [3]: pd.options.display.max_rows = 999
```

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```
In [4]: pd.options.display.max_rows
Out[4]: 999
```

The API is composed of 5 relevant functions, available directly from the `pandas` namespace:

- *`get_option()`* / *`set_option()`* - get/set the value of a single option.
- *`reset_option()`* - reset one or more options to their default value.
- *`describe_option()`* - print the descriptions of one or more options.
- *`option_context()`* - execute a codeblock with a set of options that revert to prior settings after execution.

Note: Developers can check out pandas/core/config.py for more information.

All of the functions above accept a regexp pattern (`re.search` style) as an argument, and so passing in a substring will work - as long as it is unambiguous:

```
In [5]: pd.get_option("display.max_rows")
Out[5]: 999

In [6]: pd.set_option("display.max_rows", 101)

In [7]: pd.get_option("display.max_rows")
Out[7]: 101

In [8]: pd.set_option("max_r", 102)

In [9]: pd.get_option("display.max_rows")
Out[9]: 102
```

The following will **not work** because it matches multiple option names, e.g. `display.max_colwidth`, `display.max_rows`, `display.max_columns`:

```
In [10]: try:
   ....:     pd.get_option("column")
   ....: except KeyError as e:
   ....:     print(e)
   ....:
'Pattern matched multiple keys'
```

Note: Using this form of shorthand may cause your code to break if new options with similar names are added in future versions.

You can get a list of available options and their descriptions with `describe_option`. When called with no argument `describe_option` will print out the descriptions for all available options.

2.22.2 Getting and setting options

As described above, *`get_option()`* and *`set_option()`* are available from the pandas namespace. To change an option, call `set_option('option regex', new_value)`.

```
In [11]: pd.get_option("mode.sim_interactive")
Out[11]: False

In [12]: pd.set_option("mode.sim_interactive", True)
```

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```
In [13]: pd.get_option("mode.sim_interactive")
Out[13]: True
```

Note: The option 'mode.sim_interactive' is mostly used for debugging purposes.

All options also have a default value, and you can use `reset_option` to do just that:

```
In [14]: pd.get_option("display.max_rows")
Out[14]: 60

In [15]: pd.set_option("display.max_rows", 999)

In [16]: pd.get_option("display.max_rows")
Out[16]: 999

In [17]: pd.reset_option("display.max_rows")

In [18]: pd.get_option("display.max_rows")
Out[18]: 60
```

It's also possible to reset multiple options at once (using a regex):

```
In [19]: pd.reset_option("^display")
```

`option_context` context manager has been exposed through the top-level API, allowing you to execute code with given option values. Option values are restored automatically when you exit the `with` block:

```
In [20]: with pd.option_context("display.max_rows", 10, "display.max_columns", 5):
   ....:     print(pd.get_option("display.max_rows"))
   ....:     print(pd.get_option("display.max_columns"))
   ....:
10
5

In [21]: print(pd.get_option("display.max_rows"))
60

In [22]: print(pd.get_option("display.max_columns"))
0
```

2.22.3 Setting startup options in Python/IPython environment

Using startup scripts for the Python/IPython environment to import pandas and set options makes working with pandas more efficient. To do this, create a .py or .ipy script in the startup directory of the desired profile. An example where the startup folder is in a default IPython profile can be found at:

```
$IPYTHONDIR/profile_default/startup
```

More information can be found in the IPython documentation. An example startup script for pandas is displayed below:

```
import pandas as pd

pd.set_option("display.max_rows", 999)
pd.set_option("precision", 5)
```

2.22.4 Frequently used options

The following is a walk-through of the more frequently used display options.

`display.max_rows` and `display.max_columns` sets the maximum number of rows and columns displayed when a frame is pretty-printed. Truncated lines are replaced by an ellipsis.

```
In [23]: df = pd.DataFrame(np.random.randn(7, 2))

In [24]: pd.set_option("max_rows", 7)

In [25]: df
Out[25]:
          0         1
0  0.469112 -0.282863
1 -1.509059 -1.135632
2  1.212112 -0.173215
3  0.119209 -1.044236
4 -0.861849 -2.104569
5 -0.494929  1.071804
6  0.721555 -0.706771

In [26]: pd.set_option("max_rows", 5)

In [27]: df
Out[27]:
          0         1
0   0.469112 -0.282863
1  -1.509059 -1.135632
..       ...       ...
5  -0.494929  1.071804
6   0.721555 -0.706771

[7 rows x 2 columns]

In [28]: pd.reset_option("max_rows")
```

Once the `display.max_rows` is exceeded, the `display.min_rows` options determines how many rows are shown in the truncated repr.

```
In [29]: pd.set_option("max_rows", 8)

In [30]: pd.set_option("min_rows", 4)

# below max_rows -> all rows shown
In [31]: df = pd.DataFrame(np.random.randn(7, 2))

In [32]: df
Out[32]:
          0         1
0 -1.039575  0.271860
1 -0.424972  0.567020
2  0.276232 -1.087401
3 -0.673690  0.113648
4 -1.478427  0.524988
5  0.404705  0.577046
6 -1.715002 -1.039268
```

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```
# above max_rows -> only min_rows (4) rows shown
In [33]: df = pd.DataFrame(np.random.randn(9, 2))

In [34]: df
Out[34]:
          0         1
0  -0.370647 -1.157892
1  -1.344312  0.844885
..       ...       ...
7   0.276662 -0.472035
8  -0.013960 -0.362543

[9 rows x 2 columns]

In [35]: pd.reset_option("max_rows")

In [36]: pd.reset_option("min_rows")
```

`display.expand_frame_repr` allows for the representation of dataframes to stretch across pages, wrapped over the full column vs row-wise.

```
In [37]: df = pd.DataFrame(np.random.randn(5, 10))

In [38]: pd.set_option("expand_frame_repr", True)

In [39]: df
Out[39]:
          0         1         2         3         4         5         6         7
↪    8         9
0 -0.006154 -0.923061  0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.
↪170299 -0.226169
1  0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127 -1.436737 -1.
↪413681  1.607920
2  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747 -0.410001 -0.078638  0.
↪545952 -1.219217
3 -1.226825  0.769804 -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734  0.
↪959726 -1.110336
4 -0.619976  0.149748 -0.732339  0.687738  0.176444  0.403310 -0.154951  0.301624 -2.
↪179861 -1.369849

In [40]: pd.set_option("expand_frame_repr", False)

In [41]: df
Out[41]:
          0         1         2         3         4         5         6         7
↪    8         9
0 -0.006154 -0.923061  0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.
↪170299 -0.226169
1  0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127 -1.436737 -1.
↪413681  1.607920
2  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747 -0.410001 -0.078638  0.
↪545952 -1.219217
3 -1.226825  0.769804 -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734  0.
↪959726 -1.110336
4 -0.619976  0.149748 -0.732339  0.687738  0.176444  0.403310 -0.154951  0.301624 -2.
↪179861 -1.369849
```

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```
In [42]: pd.reset_option("expand_frame_repr")
```

`display.large_repr` lets you select whether to display dataframes that exceed `max_columns` or `max_rows` as a truncated frame, or as a summary.

```
In [43]: df = pd.DataFrame(np.random.randn(10, 10))

In [44]: pd.set_option("max_rows", 5)

In [45]: pd.set_option("large_repr", "truncate")

In [46]: df
Out[46]:
           0         1         2         3         4         5         6         7  ␣
↪     8         9
0  -0.954208  1.462696 -1.743161 -0.826591 -0.345352  1.314232  0.690579  0.995761  2.
↪396780  0.014871
1   3.357427 -0.317441 -1.236269  0.896171 -0.487602 -0.082240 -2.182937  0.380396  0.
↪084844  0.432390
..       ...       ...       ...       ...       ...       ...       ...       ...  ␣
↪   ...       ...
8  -0.303421 -0.858447  0.306996 -0.028665  0.384316  1.574159  1.588931  0.476720  0.
↪473424 -0.242861
9  -0.014805 -0.284319  0.650776 -1.461665 -1.137707 -0.891060 -0.693921  1.613616  0.
↪464000  0.227371

[10 rows x 10 columns]

In [47]: pd.set_option("large_repr", "info")

In [48]: df
Out[48]:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       10 non-null     float64
 1   1       10 non-null     float64
 2   2       10 non-null     float64
 3   3       10 non-null     float64
 4   4       10 non-null     float64
 5   5       10 non-null     float64
 6   6       10 non-null     float64
 7   7       10 non-null     float64
 8   8       10 non-null     float64
 9   9       10 non-null     float64
dtypes: float64(10)
memory usage: 928.0 bytes

In [49]: pd.reset_option("large_repr")

In [50]: pd.reset_option("max_rows")
```

`display.max_colwidth` sets the maximum width of columns. Cells of this length or longer will be truncated with an ellipsis.

```
In [51]: df = pd.DataFrame(
   ....:     np.array(
   ....:         [
   ....:             ["foo", "bar", "bim", "uncomfortably long string"],
   ....:             ["horse", "cow", "banana", "apple"],
   ....:         ]
   ....:     )
   ....: )
   ....:

In [52]: pd.set_option("max_colwidth", 40)

In [53]: df
Out[53]:
       0    1       2                           3
0    foo  bar     bim  uncomfortably long string
1  horse  cow  banana                       apple

In [54]: pd.set_option("max_colwidth", 6)

In [55]: df
Out[55]:
       0    1      2      3
0    foo  bar    bim  un...
1  horse  cow  ba...  apple

In [56]: pd.reset_option("max_colwidth")
```

`display.max_info_columns` sets a threshold for when by-column info will be given.

```
In [57]: df = pd.DataFrame(np.random.randn(10, 10))

In [58]: pd.set_option("max_info_columns", 11)

In [59]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       10 non-null     float64
 1   1       10 non-null     float64
 2   2       10 non-null     float64
 3   3       10 non-null     float64
 4   4       10 non-null     float64
 5   5       10 non-null     float64
 6   6       10 non-null     float64
 7   7       10 non-null     float64
 8   8       10 non-null     float64
 9   9       10 non-null     float64
dtypes: float64(10)
memory usage: 928.0 bytes

In [60]: pd.set_option("max_info_columns", 5)

In [61]: df.info()
<class 'pandas.core.frame.DataFrame'>
```

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```
RangeIndex: 10 entries, 0 to 9
Columns: 10 entries, 0 to 9
dtypes: float64(10)
memory usage: 928.0 bytes

In [62]: pd.reset_option("max_info_columns")
```

`display.max_info_rows`: `df.info()` will usually show null-counts for each column. For large frames this can be quite slow. `max_info_rows` and `max_info_cols` limit this null check only to frames with smaller dimensions then specified. Note that you can specify the option `df.info(null_counts=True)` to override on showing a particular frame.

```
In [63]: df = pd.DataFrame(np.random.choice([0, 1, np.nan], size=(10, 10)))

In [64]: df
Out[64]:
     0    1    2    3    4    5    6    7    8    9
0  0.0  NaN  1.0  NaN  NaN  0.0  NaN  0.0  NaN  1.0
1  1.0  NaN  1.0  1.0  1.0  1.0  NaN  0.0  0.0  NaN
2  0.0  NaN  1.0  0.0  0.0  NaN  NaN  NaN  NaN  0.0
3  NaN  NaN  NaN  0.0  1.0  1.0  NaN  1.0  NaN  1.0
4  0.0  NaN  NaN  NaN  0.0  NaN  NaN  NaN  1.0  0.0
5  0.0  1.0  1.0  1.0  1.0  0.0  NaN  NaN  1.0  0.0
6  1.0  1.0  1.0  NaN  1.0  NaN  1.0  0.0  NaN  NaN
7  0.0  0.0  1.0  0.0  1.0  0.0  1.0  1.0  0.0  NaN
8  NaN  NaN  NaN  0.0  NaN  NaN  NaN  NaN  1.0  NaN
9  0.0  NaN  0.0  NaN  NaN  0.0  NaN  1.0  1.0  0.0

In [65]: pd.set_option("max_info_rows", 11)

In [66]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       8 non-null      float64
 1   1       3 non-null      float64
 2   2       7 non-null      float64
 3   3       6 non-null      float64
 4   4       7 non-null      float64
 5   5       6 non-null      float64
 6   6       2 non-null      float64
 7   7       6 non-null      float64
 8   8       6 non-null      float64
 9   9       6 non-null      float64
dtypes: float64(10)
memory usage: 928.0 bytes

In [67]: pd.set_option("max_info_rows", 5)

In [68]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column  Dtype
```

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```
---  ------  -----
 0   0       float64
 1   1       float64
 2   2       float64
 3   3       float64
 4   4       float64
 5   5       float64
 6   6       float64
 7   7       float64
 8   8       float64
 9   9       float64
dtypes: float64(10)
memory usage: 928.0 bytes

In [69]: pd.reset_option("max_info_rows")
```

`display.precision` sets the output display precision in terms of decimal places. This is only a suggestion.

```
In [70]: df = pd.DataFrame(np.random.randn(5, 5))

In [71]: pd.set_option("precision", 7)

In [72]: df
Out[72]:
           0          1          2          3          4
0 -1.1506406 -0.7983341 -0.5576966  0.3813531  1.3371217
1 -1.5310949  1.3314582 -0.5713290 -0.0266708 -1.0856630
2 -1.1147378 -0.0582158 -0.4867681  1.6851483  0.1125723
3 -1.4953086  0.8984347 -0.1482168 -1.5960698  0.1596530
4  0.2621358  0.0362196  0.1847350 -0.2550694 -0.2710197

In [73]: pd.set_option("precision", 4)

In [74]: df
Out[74]:
        0       1       2       3       4
0 -1.1506 -0.7983 -0.5577  0.3814  1.3371
1 -1.5311  1.3315 -0.5713 -0.0267 -1.0857
2 -1.1147 -0.0582 -0.4868  1.6851  0.1126
3 -1.4953  0.8984 -0.1482 -1.5961  0.1597
4  0.2621  0.0362  0.1847 -0.2551 -0.2710
```

`display.chop_threshold` sets at what level pandas rounds to zero when it displays a Series of DataFrame. This setting does not change the precision at which the number is stored.

```
In [75]: df = pd.DataFrame(np.random.randn(6, 6))

In [76]: pd.set_option("chop_threshold", 0)

In [77]: df
Out[77]:
        0       1       2       3       4       5
0  1.2884  0.2946 -1.1658  0.8470 -0.6856  0.6091
1 -0.3040  0.6256 -0.0593  0.2497  1.1039 -1.0875
2  1.9980 -0.2445  0.1362  0.8863 -1.3507 -0.8863
3 -1.0133  1.9209 -0.3882 -2.3144  0.6655  0.4026
```

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```
4  0.3996 -1.7660  0.8504  0.3881  0.9923  0.7441
5 -0.7398 -1.0549 -0.1796  0.6396  1.5850  1.9067

In [78]: pd.set_option("chop_threshold", 0.5)

In [79]: df
Out[79]:
        0       1       2       3       4       5
0  1.2884  0.0000 -1.1658  0.8470 -0.6856  0.6091
1  0.0000  0.6256  0.0000  0.0000  1.1039 -1.0875
2  1.9980  0.0000  0.0000  0.8863 -1.3507 -0.8863
3 -1.0133  1.9209  0.0000 -2.3144  0.6655  0.0000
4  0.0000 -1.7660  0.8504  0.0000  0.9923  0.7441
5 -0.7398 -1.0549  0.0000  0.6396  1.5850  1.9067

In [80]: pd.reset_option("chop_threshold")
```

`display.colheader_justify` controls the justification of the headers. The options are 'right', and 'left'.

```
In [81]: df = pd.DataFrame(
   ....:     np.array([np.random.randn(6), np.random.randint(1, 9, 6) * 0.1, np.
↪zeros(6)]).T,
   ....:     columns=["A", "B", "C"],
   ....:     dtype="float",
   ....: )
   ....:

In [82]: pd.set_option("colheader_justify", "right")

In [83]: df
Out[83]:
        A    B    C
0  0.1040  0.1  0.0
1  0.1741  0.5  0.0
2 -0.4395  0.4  0.0
3 -0.7413  0.8  0.0
4 -0.0797  0.4  0.0
5 -0.9229  0.3  0.0

In [84]: pd.set_option("colheader_justify", "left")

In [85]: df
Out[85]:
   A       B    C
0  0.1040  0.1  0.0
1  0.1741  0.5  0.0
2 -0.4395  0.4  0.0
3 -0.7413  0.8  0.0
4 -0.0797  0.4  0.0
5 -0.9229  0.3  0.0

In [86]: pd.reset_option("colheader_justify")
```

2.22.5 Available options

Option	Default	Function
display.chop_threshold	None	If set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends.
display.colheader_justify	right	Controls the justification of column headers. used by DataFrameFormatter.
display.column_space	12	No description available.
display.date_dayfirst	False	When True, prints and parses dates with the day first, eg 20/01/2005
display.date_yearfirst	False	When True, prints and parses dates with the year first, eg 2005/01/20
display.encoding	UTF-8	Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console.
display.expand_frame_repr	True	Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, `max_columns` is still respected, but the output will wrap-around across multiple "pages" if its width exceeds `display.width`.
display.float_format	None	The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See core.format.EngFormatter for an example.
display.large_repr	truncate	For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default), or switch to the view from df.info() (the behaviour in earlier versions of pandas). allowable settings, ['truncate', 'info']
display.latex.repr	False	Whether to produce a latex DataFrame representation for Jupyter frontends that support it.
display.latex.escape	True	Escapes special characters in DataFrames, when using the to_latex method.
display.latex.longtable	False	Specifies if the to_latex method of a DataFrame uses the longtable format.

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Option	Default	Function
display.latex.multicolumn	True	Combines columns when using a MultiIndex
display.latex.multicolumn_format	'l'	Alignment of multicolumn labels
display.latex.multirow	False	Combines rows when using a MultiIndex. Centered instead of top-aligned, separated by clines.
display.max_columns	0 or 20	max_rows and max_columns are used in __repr__() methods to decide if to_string() or info() is used to render an object to a string. In case Python/IPython is running in a terminal this is set to 0 by default and pandas will correctly auto-detect the width of the terminal and switch to a smaller format in case all columns would not fit vertically. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection, in which case the default is set to 20. 'None' value means unlimited.
display.max_colwidth	50	The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. 'None' value means unlimited.
display.max_info_columns	100	max_info_columns is used in DataFrame.info method to decide if per column information will be printed.
display.max_info_rows	1690785	df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions then specified.
display.max_rows	60	This sets the maximum number of rows pandas should output when printing out various output. For example, this value determines whether the repr() for a dataframe prints out fully or just a truncated or summary repr. 'None' value means unlimited.

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Option	Default	Function
display.min_rows	10	The numbers of rows to show in a truncated repr (when `max_rows` is exceeded). Ignored when `max_rows` is set to None or 0. When set to None, follows the value of `max_rows`.
display.max_seq_items	100	when pretty-printing a long sequence, no more then `max_seq_items` will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string. If set to None, the number of items to be printed is unlimited.
display.memory_usage	True	This specifies if the memory usage of a DataFrame should be displayed when the df.info() method is invoked.
display.multi_sparse	True	"Sparsify" MultiIndex display (don't display repeated elements in outer levels within groups)
display.notebook_repr_html	True	When True, IPython notebook will use html representation for pandas objects (if it is available).
display.pprint_nest_depth	3	Controls the number of nested levels to process when pretty-printing
display.precision	6	Floating point output precision in terms of number of places after the decimal, for regular formatting as well as scientific notation. Similar to numpy's `precision` print option
display.show_dimensions	truncate	Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns)
display.width	80	Width of the display in characters. In case Python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width.
display.html.table_schema	False	Whether to publish a Table Schema representation for frontends that support it.

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Option	Default	Function
display.html.border	1	A `border=value` attribute is inserted in the `<table>` tag for the DataFrame HTML repr.
display.html.use_mathjax	True	When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol.
io.excel.xls.writer	xlwt	The default Excel writer engine for 'xls' files. Deprecated since version 1.2.0: As xlwt package is no longer maintained, the `xlwt` engine will be removed in a future version of pandas. Since this is the only engine in pandas that supports writing to `.xls` files, this option will also be removed.
io.excel.xlsm.writer	openpyxl	The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default).
io.excel.xlsx.writer	openpyxl	The default Excel writer engine for 'xlsx' files.
io.hdf.default_format	None	default format writing format, if None, then put will default to 'fixed' and append will default to 'table'
io.hdf.dropna_table	True	drop ALL nan rows when appending to a table
io.parquet.engine	None	The engine to use as a default for parquet reading and writing. If None then try 'pyarrow' and 'fastparquet'
mode.chained_assignment	warn	Controls `SettingWithCopyWarning`: 'raise', 'warn', or None. Raise an exception, warn, or no action if trying to use *chained assignment*.
mode.sim_interactive	False	Whether to simulate interactive mode for purposes of testing.
mode.use_inf_as_na	False	True means treat None, NaN, -INF, INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way).
compute.use_bottleneck	True	Use the bottleneck library to accelerate computation if it is installed.
compute.use_numexpr	True	Use the numexpr library to accelerate computation if it is installed.

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Option	Default	Function
plotting.backend	matplotlib	Change the plotting backend to a different backend than the current matplotlib one. Backends can be implemented as third-party libraries implementing the pandas plotting API. They can use other plotting libraries like Bokeh, Altair, etc.
plotting.matplotlib.register_converters	True	Register custom converters with matplotlib. Set to False to de-register.

2.22.6 Number formatting

pandas also allows you to set how numbers are displayed in the console. This option is not set through the `set_options` API.

Use the `set_eng_float_format` function to alter the floating-point formatting of pandas objects to produce a particular format.

For instance:

```
In [87]: import numpy as np

In [88]: pd.set_eng_float_format(accuracy=3, use_eng_prefix=True)

In [89]: s = pd.Series(np.random.randn(5), index=["a", "b", "c", "d", "e"])

In [90]: s / 1.0e3
Out[90]:
a    303.638u
b   -721.084u
c   -622.696u
d    648.250u
e     -1.945m
dtype: float64

In [91]: s / 1.0e6
Out[91]:
a    303.638n
b   -721.084n
c   -622.696n
d    648.250n
e     -1.945u
dtype: float64
```

To round floats on a case-by-case basis, you can also use *round()* and *round()*.

2.22.7 Unicode formatting

Warning: Enabling this option will affect the performance for printing of DataFrame and Series (about 2 times slower). Use only when it is actually required.

Some East Asian countries use Unicode characters whose width corresponds to two Latin characters. If a DataFrame or Series contains these characters, the default output mode may not align them properly.

Note: Screen captures are attached for each output to show the actual results.

```
In [92]: df = pd.DataFrame({"": ["UK", ""], "": ["Alice", ""]})

In [93]: df
Out[93]:

0  UK  Alice
1
```

```
>>> df = pd.DataFrame({u'国籍': ['UK', u'日本'], u'名前': ['Alice', u'しのぶ']})
>>> df
     名前  国籍
0  Alice  UK
1    しのぶ  日本
```

Enabling `display.unicode.east_asian_width` allows pandas to check each character's "East Asian Width" property. These characters can be aligned properly by setting this option to `True`. However, this will result in longer render times than the standard `len` function.

```
In [94]: pd.set_option("display.unicode.east_asian_width", True)

In [95]: df
Out[95]:

0    UK   Alice
1
```

```
>>> pd.set_option('display.unicode.east_asian_width', True)
>>> df
     名前  国籍
0   Alice   UK
1  しのぶ  日本
```

In addition, Unicode characters whose width is "Ambiguous" can either be 1 or 2 characters wide depending on the terminal setting or encoding. The option `display.unicode.ambiguous_as_wide` can be used to handle the ambiguity.

By default, an "Ambiguous" character's width, such as "¡" (inverted exclamation) in the example below, is taken to be 1.

```
In [96]: df = pd.DataFrame({"a": ["xxx", "¡¡"], "b": ["yyy", "¡¡"]})

In [97]: df
Out[97]:
     a    b
```

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```
0  xxx  yyy
1   ¡¡   ¡¡
```

```
>>> df = pd.DataFrame({'a': ['xxx', u'¡¡'], 'b': ['yyy', u'¡¡']})
>>> df
     a    b
0  xxx  yyy
1   ¡¡   ¡¡
```

Enabling `display.unicode.ambiguous_as_wide` makes pandas interpret these characters' widths to be 2. (Note that this option will only be effective when `display.unicode.east_asian_width` is enabled.)

However, setting this option incorrectly for your terminal will cause these characters to be aligned incorrectly:

```
In [98]: pd.set_option("display.unicode.ambiguous_as_wide", True)

In [99]: df
Out[99]:
      a     b
0   xxx   yyy
1  ¡¡   ¡¡
```

```
>>> pd.set_option('display.unicode.ambiguous_as_wide', True)
>>> df
      a     b
0   xxx   yyy
1  ¡¡  ¡¡
```

2.22.8 Table schema display

`DataFrame` and `Series` will publish a Table Schema representation by default. False by default, this can be enabled globally with the `display.html.table_schema` option:

```
In [100]: pd.set_option("display.html.table_schema", True)
```

Only `'display.max_rows'` are serialized and published.

2.23 Enhancing performance

In this part of the tutorial, we will investigate how to speed up certain functions operating on pandas `DataFrames` using three different techniques: Cython, Numba and *`pandas.eval()`*. We will see a speed improvement of ~200 when we use Cython and Numba on a test function operating row-wise on the `DataFrame`. Using *`pandas.eval()`* we will speed up a sum by an order of ~2.

Note: In addition to following the steps in this tutorial, users interested in enhancing performance are highly encouraged to install the *recommended dependencies* for pandas. These dependencies are often not installed by default, but will offer speed improvements if present.

2.23.1 Cython (writing C extensions for pandas)

For many use cases writing pandas in pure Python and NumPy is sufficient. In some computationally heavy applications however, it can be possible to achieve sizable speed-ups by offloading work to cython.

This tutorial assumes you have refactored as much as possible in Python, for example by trying to remove for-loops and making use of NumPy vectorization. It's always worth optimising in Python first.

This tutorial walks through a "typical" process of cythonizing a slow computation. We use an example from the Cython documentation but in the context of pandas. Our final cythonized solution is around 100 times faster than the pure Python solution.

Pure Python

We have a `DataFrame` to which we want to apply a function row-wise.

```
In [1]: df = pd.DataFrame(
   ...:     {
   ...:         "a": np.random.randn(1000),
   ...:         "b": np.random.randn(1000),
   ...:         "N": np.random.randint(100, 1000, (1000)),
   ...:         "x": "x",
   ...:     }
   ...: )
   ...:

In [2]: df
Out[2]:
            a         b    N  x
0    0.469112 -0.218470  585  x
1   -0.282863 -0.061645  841  x
2   -1.509059 -0.723780  251  x
3   -1.135632  0.551225  972  x
4    1.212112 -0.497767  181  x
..        ...       ...  ... ..
995 -1.512743  0.874737  374  x
996  0.933753  1.120790  246  x
997 -0.308013  0.198768  157  x
998 -0.079915  1.757555  977  x
999 -1.010589 -1.115680  770  x

[1000 rows x 4 columns]
```

Here's the function in pure Python:

```
In [3]: def f(x):
   ...:     return x * (x - 1)
   ...:

In [4]: def integrate_f(a, b, N):
   ...:     s = 0
   ...:     dx = (b - a) / N
   ...:     for i in range(N):
   ...:         s += f(a + i * dx)
   ...:     return s * dx
   ...:
```

We achieve our result by using `apply` (row-wise):

```
In [7]: %timeit df.apply(lambda x: integrate_f(x["a"], x["b"], x["N"]), axis=1)
10 loops, best of 3: 174 ms per loop
```

But clearly this isn't fast enough for us. Let's take a look and see where the time is spent during this operation (limited to the most time consuming four calls) using the prun ipython magic function:

```
In [5]: %prun -l 4 df.apply(lambda x: integrate_f(x["a"], x["b"], x["N"]), axis=1)  #␣
↪noqa E999
         627853 function calls (627832 primitive calls) in 0.145 seconds

   Ordered by: internal time
   List reduced from 217 to 4 due to restriction <4>

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     1000    0.080    0.000    0.116    0.000 <ipython-input-4-c2a74e076cf0>:
↪1(integrate_f)
   552423    0.037    0.000    0.037    0.000 <ipython-input-3-c138bdd570e3>:1(f)
     3000    0.004    0.000    0.018    0.000 series.py:837(__getitem__)
     3000    0.002    0.000    0.013    0.000 series.py:942(_get_value)
```

By far the majority of time is spend inside either `integrate_f` or `f`, hence we'll concentrate our efforts cythonizing these two functions.

Plain Cython

First we're going to need to import the Cython magic function to IPython:

```
In [6]: %load_ext Cython
```

Now, let's simply copy our functions over to Cython as is (the suffix is here to distinguish between function versions):

```
In [7]: %%cython
   ...: def f_plain(x):
   ...:     return x * (x - 1)
   ...: def integrate_f_plain(a, b, N):
   ...:     s = 0
   ...:     dx = (b - a) / N
   ...:     for i in range(N):
   ...:         s += f_plain(a + i * dx)
   ...:     return s * dx
   ...:
```

Note: If you're having trouble pasting the above into your ipython, you may need to be using bleeding edge IPython for paste to play well with cell magics.

```
In [4]: %timeit df.apply(lambda x: integrate_f_plain(x["a"], x["b"], x["N"]), axis=1)
10 loops, best of 3: 85.5 ms per loop
```

Already this has shaved a third off, not too bad for a simple copy and paste.

Adding type

We get another huge improvement simply by providing type information:

```
In [8]: %%cython
   ...: cdef double f_typed(double x) except? -2:
   ...:     return x * (x - 1)
   ...: cpdef double integrate_f_typed(double a, double b, int N):
   ...:     cdef int i
   ...:     cdef double s, dx
   ...:     s = 0
   ...:     dx = (b - a) / N
   ...:     for i in range(N):
   ...:         s += f_typed(a + i * dx)
   ...:     return s * dx
   ...:
```

```
In [4]: %timeit df.apply(lambda x: integrate_f_typed(x["a"], x["b"], x["N"]), axis=1)
10 loops, best of 3: 20.3 ms per loop
```

Now, we're talking! It's now over ten times faster than the original Python implementation, and we haven't *really* modified the code. Let's have another look at what's eating up time:

```
In [9]: %prun -l 4 df.apply(lambda x: integrate_f_typed(x["a"], x["b"], x["N"]),␣
↪axis=1)
         75423 function calls (75402 primitive calls) in 0.026 seconds

   Ordered by: internal time
   List reduced from 214 to 4 due to restriction <4>

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     3000    0.003    0.000    0.016    0.000 series.py:837(__getitem__)
     3000    0.002    0.000    0.011    0.000 series.py:942(_get_value)
     3000    0.001    0.000    0.005    0.000 base.py:3036(get_loc)
     3000    0.001    0.000    0.003    0.000 base.py:5287(_maybe_cast_indexer)
```

Using ndarray

It's calling series... a lot! It's creating a Series from each row, and get-ting from both the index and the series (three times for each row). Function calls are expensive in Python, so maybe we could minimize these by cythonizing the apply part.

Note: We are now passing ndarrays into the Cython function, fortunately Cython plays very nicely with NumPy.

```
In [10]: %%cython
   ....: cimport numpy as np
   ....: import numpy as np
   ....: cdef double f_typed(double x) except? -2:
   ....:     return x * (x - 1)
   ....: cpdef double integrate_f_typed(double a, double b, int N):
   ....:     cdef int i
   ....:     cdef double s, dx
   ....:     s = 0
   ....:     dx = (b - a) / N
```

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```
   ....:     for i in range(N):
   ....:         s += f_typed(a + i * dx)
   ....:     return s * dx
   ....: cpdef np.ndarray[double] apply_integrate_f(np.ndarray col_a, np.ndarray col_
↪b,
   ....:                                            np.ndarray col_N):
   ....:     assert (col_a.dtype == np.float_
   ....:             and col_b.dtype == np.float_ and col_N.dtype == np.int_)
   ....:     cdef Py_ssize_t i, n = len(col_N)
   ....:     assert (len(col_a) == len(col_b) == n)
   ....:     cdef np.ndarray[double] res = np.empty(n)
   ....:     for i in range(len(col_a)):
   ....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
   ....:     return res
   ....:
```

The implementation is simple, it creates an array of zeros and loops over the rows, applying our `integrate_f_typed`, and putting this in the zeros array.

Warning: You can **not pass** a `Series` directly as a `ndarray` typed parameter to a Cython function. Instead pass the actual `ndarray` using the *`Series.to_numpy()`*. The reason is that the Cython definition is specific to an ndarray and not the passed `Series`.

So, do not do this:

```
apply_integrate_f(df["a"], df["b"], df["N"])
```

But rather, use *`Series.to_numpy()`* to get the underlying `ndarray`:

```
apply_integrate_f(df["a"].to_numpy(), df["b"].to_numpy(), df["N"].to_numpy())
```

Note: Loops like this would be *extremely* slow in Python, but in Cython looping over NumPy arrays is *fast*.

```
In [4]: %timeit apply_integrate_f(df["a"].to_numpy(), df["b"].to_numpy(), df["N"].to_
↪numpy())
1000 loops, best of 3: 1.25 ms per loop
```

We've gotten another big improvement. Let's check again where the time is spent:

```
In [11]: %%prun -l 4 apply_integrate_f(df["a"].to_numpy(), df["b"].to_numpy(), df["N
↪"].to_numpy())
```

As one might expect, the majority of the time is now spent in `apply_integrate_f`, so if we wanted to make anymore efficiencies we must continue to concentrate our efforts here.

More advanced techniques

There is still hope for improvement. Here's an example of using some more advanced Cython techniques:

```
In [12]: %%cython
   ....: cimport cython
   ....: cimport numpy as np
   ....: import numpy as np
   ....: cdef double f_typed(double x) except? -2:
   ....:     return x * (x - 1)
   ....: cpdef double integrate_f_typed(double a, double b, int N):
   ....:     cdef int i
   ....:     cdef double s, dx
   ....:     s = 0
   ....:     dx = (b - a) / N
   ....:     for i in range(N):
   ....:         s += f_typed(a + i * dx)
   ....:     return s * dx
   ....: @cython.boundscheck(False)
   ....: @cython.wraparound(False)
   ....: cpdef np.ndarray[double] apply_integrate_f_wrap(np.ndarray[double] col_a,
   ....:                                                 np.ndarray[double] col_b,
   ....:                                                 np.ndarray[int] col_N):
   ....:     cdef int i, n = len(col_N)
   ....:     assert len(col_a) == len(col_b) == n
   ....:     cdef np.ndarray[double] res = np.empty(n)
   ....:     for i in range(n):
   ....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
   ....:     return res
   ....:
```

```
In [4]: %timeit apply_integrate_f_wrap(df["a"].to_numpy(), df["b"].to_numpy(), df["N
↪"].to_numpy())
1000 loops, best of 3: 987 us per loop
```

Even faster, with the caveat that a bug in our Cython code (an off-by-one error, for example) might cause a segfault because memory access isn't checked. For more about `boundscheck` and `wraparound`, see the Cython docs on compiler directives.

2.23.2 Using Numba

A recent alternative to statically compiling Cython code, is to use a *dynamic jit-compiler*, Numba.

Numba gives you the power to speed up your applications with high performance functions written directly in Python. With a few annotations, array-oriented and math-heavy Python code can be just-in-time compiled to native machine instructions, similar in performance to C, C++ and Fortran, without having to switch languages or Python interpreters.

Numba works by generating optimized machine code using the LLVM compiler infrastructure at import time, runtime, or statically (using the included pycc tool). Numba supports compilation of Python to run on either CPU or GPU hardware, and is designed to integrate with the Python scientific software stack.

Note: You will need to install Numba. This is easy with `conda`, by using: `conda install numba`, see *installing using miniconda*.

Note: As of Numba version 0.20, pandas objects cannot be passed directly to Numba-compiled functions. Instead, one must pass the NumPy array underlying the pandas object to the Numba-compiled function as demonstrated below.

Jit

We demonstrate how to use Numba to just-in-time compile our code. We simply take the plain Python code from above and annotate with the `@jit` decorator.

```
import numba


@numba.jit
def f_plain(x):
    return x * (x - 1)


@numba.jit
def integrate_f_numba(a, b, N):
    s = 0
    dx = (b - a) / N
    for i in range(N):
        s += f_plain(a + i * dx)
    return s * dx


@numba.jit
def apply_integrate_f_numba(col_a, col_b, col_N):
    n = len(col_N)
    result = np.empty(n, dtype="float64")
    assert len(col_a) == len(col_b) == n
    for i in range(n):
        result[i] = integrate_f_numba(col_a[i], col_b[i], col_N[i])
    return result


def compute_numba(df):
    result = apply_integrate_f_numba(
        df["a"].to_numpy(), df["b"].to_numpy(), df["N"].to_numpy()
    )
    return pd.Series(result, index=df.index, name="result")
```

Note that we directly pass NumPy arrays to the Numba function. `compute_numba` is just a wrapper that provides a nicer interface by passing/returning pandas objects.

```
In [4]: %timeit compute_numba(df)
1000 loops, best of 3: 798 us per loop
```

In this example, using Numba was faster than Cython.

Numba as an argument

Additionally, we can leverage the power of Numba by calling it as an argument in `apply()`. See *Computation tools* for an extensive example.

Vectorize

Numba can also be used to write vectorized functions that do not require the user to explicitly loop over the observations of a vector; a vectorized function will be applied to each row automatically. Consider the following toy example of doubling each observation:

```
import numba


def double_every_value_nonumba(x):
    return x * 2


@numba.vectorize
def double_every_value_withnumba(x):  # noqa E501
    return x * 2
```

```
# Custom function without numba
In [5]: %timeit df["col1_doubled"] = df["a"].apply(double_every_value_nonumba)  #␣
↪noqa E501
1000 loops, best of 3: 797 us per loop

# Standard implementation (faster than a custom function)
In [6]: %timeit df["col1_doubled"] = df["a"] * 2
1000 loops, best of 3: 233 us per loop

# Custom function with numba
In [7]: %timeit df["col1_doubled"] = double_every_value_withnumba(df["a"].to_numpy())
1000 loops, best of 3: 145 us per loop
```

Caveats

Note: Numba will execute on any function, but can only accelerate certain classes of functions.

Numba is best at accelerating functions that apply numerical functions to NumPy arrays. When passed a function that only uses operations it knows how to accelerate, it will execute in `nopython` mode.

If Numba is passed a function that includes something it doesn't know how to work with – a category that currently includes sets, lists, dictionaries, or string functions – it will revert to `object mode`. In `object mode`, Numba will execute but your code will not speed up significantly. If you would prefer that Numba throw an error if it cannot compile a function in a way that speeds up your code, pass Numba the argument `nopython=True` (e.g. `@numba.jit(nopython=True)`). For more on troubleshooting Numba modes, see the Numba troubleshooting page.

Read more in the Numba docs.

2.23.3 Expression evaluation via `eval()`

The top-level function *pandas.eval()* implements expression evaluation of *Series* and *DataFrame* objects.

Note: To benefit from using *eval()* you need to install `numexpr`. See the *recommended dependencies section* for more details.

The point of using *eval()* for expression evaluation rather than plain Python is two-fold: 1) large *DataFrame* objects are evaluated more efficiently and 2) large arithmetic and boolean expressions are evaluated all at once by the underlying engine (by default `numexpr` is used for evaluation).

Note: You should not use *eval()* for simple expressions or for expressions involving small DataFrames. In fact, *eval()* is many orders of magnitude slower for smaller expressions/objects than plain ol' Python. A good rule of thumb is to only use *eval()* when you have a `DataFrame` with more than 10,000 rows.

---

eval() supports all arithmetic expressions supported by the engine in addition to some extensions available only in pandas.

Note: The larger the frame and the larger the expression the more speedup you will see from using *eval()*.

Supported syntax

These operations are supported by *pandas.eval()*:

- Arithmetic operations except for the left shift (<<) and right shift (>>) operators, e.g., `df + 2 * pi / s ** 4 % 42 - the_golden_ratio`
- Comparison operations, including chained comparisons, e.g., `2 < df < df2`
- Boolean operations, e.g., `df < df2 and df3 < df4 or not df_bool`
- `list` and `tuple` literals, e.g., `[1, 2]` or `(1, 2)`
- Attribute access, e.g., `df.a`
- Subscript expressions, e.g., `df[0]`
- Simple variable evaluation, e.g., `pd.eval("df")` (this is not very useful)
- Math functions: `sin`, `cos`, `exp`, `log`, `expm1`, `log1p`, `sqrt`, `sinh`, `cosh`, `tanh`, `arcsin`, `arccos`, `arctan`, `arccosh`, `arcsinh`, `arctanh`, `abs`, `arctan2` and `log10`.

This Python syntax is **not** allowed:

- Expressions
  - Function calls other than math functions.
  - `is`/`is not` operations
  - `if` expressions
  - `lambda` expressions
  - `list`/`set`/`dict` comprehensions
  - Literal `dict` and `set` expressions

  - `yield` expressions
  - Generator expressions
  - Boolean expressions consisting of only scalar values
- Statements
  - Neither simple nor compound statements are allowed. This includes things like `for`, `while`, and `if`.

`eval()` examples

pandas.eval() works well with expressions containing large arrays.

First let's create a few decent-sized arrays to play with:

```
In [13]: nrows, ncols = 20000, 100

In [14]: df1, df2, df3, df4 = [pd.DataFrame(np.random.randn(nrows, ncols)) for _ in␣
↪range(4)]
```

Now let's compare adding them together using plain ol' Python versus *eval()*:

```
In [15]: %timeit df1 + df2 + df3 + df4
10.5 ms +- 98.5 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [16]: %timeit pd.eval("df1 + df2 + df3 + df4")
5.22 ms +- 9.58 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Now let's do the same thing but with comparisons:

```
In [17]: %timeit (df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)
5.31 ms +- 205 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [18]: %timeit pd.eval("(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)")
5.62 ms +- 77.2 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

eval() also works with unaligned pandas objects:

```
In [19]: s = pd.Series(np.random.randn(50))

In [20]: %timeit df1 + df2 + df3 + df4 + s
19.4 ms +- 401 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [21]: %timeit pd.eval("df1 + df2 + df3 + df4 + s")
5.8 ms +- 31.2 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Note: Operations such as

```
1 and 2  # would parse to 1 & 2, but should evaluate to 2
3 or 4  # would parse to 3 | 4, but should evaluate to 3
~1  # this is okay, but slower when using eval
```

should be performed in Python. An exception will be raised if you try to perform any boolean/bitwise operations with scalar operands that are not of type `bool` or `np.bool_`. Again, you should perform these kinds of operations in plain Python.

The `DataFrame.eval` method

In addition to the top level *pandas.eval()* function you can also evaluate an expression in the "context" of a *DataFrame*.

```
In [22]: df = pd.DataFrame(np.random.randn(5, 2), columns=["a", "b"])

In [23]: df.eval("a + b")
Out[23]:
0   -0.246747
1    0.867786
2   -1.626063
3   -1.134978
4   -1.027798
dtype: float64
```

Any expression that is a valid *pandas.eval()* expression is also a valid *DataFrame.eval()* expression, with the added benefit that you don't have to prefix the name of the *DataFrame* to the column(s) you're interested in evaluating.

In addition, you can perform assignment of columns within an expression. This allows for *formulaic evaluation*. The assignment target can be a new column name or an existing column name, and it must be a valid Python identifier.

The `inplace` keyword determines whether this assignment will performed on the original `DataFrame` or return a copy with the new column.

```
In [24]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))

In [25]: df.eval("c = a + b", inplace=True)

In [26]: df.eval("d = a + b + c", inplace=True)

In [27]: df.eval("a = 1", inplace=True)

In [28]: df
Out[28]:
   a  b   c   d
0  1  5   5  10
1  1  6   7  14
2  1  7   9  18
3  1  8  11  22
4  1  9  13  26
```

When `inplace` is set to `False`, the default, a copy of the `DataFrame` with the new or modified columns is returned and the original frame is unchanged.

```
In [29]: df
Out[29]:
   a  b   c   d
0  1  5   5  10
1  1  6   7  14
2  1  7   9  18
3  1  8  11  22
4  1  9  13  26

In [30]: df.eval("e = a - c", inplace=False)
Out[30]:
   a  b   c   d   e
```

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```
0  1  5   5  10  -4
1  1  6   7  14  -6
2  1  7   9  18  -8
3  1  8  11  22 -10
4  1  9  13  26 -12

In [31]: df
Out[31]:
   a  b   c   d
0  1  5   5  10
1  1  6   7  14
2  1  7   9  18
3  1  8  11  22
4  1  9  13  26
```

As a convenience, multiple assignments can be performed by using a multi-line string.

```
In [32]: df.eval(
   ....:     """
   ....: c = a + b
   ....: d = a + b + c
   ....: a = 1""",
   ....:     inplace=False,
   ....: )
   ....:
Out[32]:
   a  b   c   d
0  1  5   6  12
1  1  6   7  14
2  1  7   8  16
3  1  8   9  18
4  1  9  10  20
```

The equivalent in standard Python would be

```
In [33]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))

In [34]: df["c"] = df["a"] + df["b"]

In [35]: df["d"] = df["a"] + df["b"] + df["c"]

In [36]: df["a"] = 1

In [37]: df
Out[37]:
   a  b   c   d
0  1  5   5  10
1  1  6   7  14
2  1  7   9  18
3  1  8  11  22
4  1  9  13  26
```

The `query` method has a `inplace` keyword which determines whether the query modifies the original frame.

```
In [38]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))

In [39]: df.query("a > 2")
```

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```
Out[39]:
   a  b
3  3  8
4  4  9

In [40]: df.query("a > 2", inplace=True)

In [41]: df
Out[41]:
   a  b
3  3  8
4  4  9
```

Local variables

You must *explicitly reference* any local variable that you want to use in an expression by placing the `@` character in front of the name. For example,

```
In [42]: df = pd.DataFrame(np.random.randn(5, 2), columns=list("ab"))

In [43]: newcol = np.random.randn(len(df))

In [44]: df.eval("b + @newcol")
Out[44]:
0   -0.173926
1    2.493083
2   -0.881831
3   -0.691045
4    1.334703
dtype: float64

In [45]: df.query("b < @newcol")
Out[45]:
          a         b
0  0.863987 -0.115998
2 -2.621419 -1.297879
```

If you don't prefix the local variable with `@`, pandas will raise an exception telling you the variable is undefined.

When using *DataFrame.eval()* and *DataFrame.query()*, this allows you to have a local variable and a *DataFrame* column with the same name in an expression.

```
In [46]: a = np.random.randn()

In [47]: df.query("@a < a")
Out[47]:
          a         b
0  0.863987 -0.115998

In [48]: df.loc[a < df["a"]]  # same as the previous expression
Out[48]:
          a         b
0  0.863987 -0.115998
```

With *pandas.eval()* you cannot use the `@` prefix *at all*, because it isn't defined in that context. pandas will let you know this if you try to use `@` in a top-level call to *pandas.eval()*. For example,

```
In [49]: a, b = 1, 2

In [50]: pd.eval("@a + b")
Traceback (most recent call last):

  File "/opt/conda/envs/pandas/lib/python3.8/site-packages/IPython/core/
↪interactiveshell.py", line 3427, in run_code
    exec(code_obj, self.user_global_ns, self.user_ns)

  File "<ipython-input-50-f23f43311349>", line 1, in <module>
    pd.eval("@a + b")

  File "/pandas/pandas/core/computation/eval.py", line 331, in eval
    _check_for_locals(expr, level, parser)

  File "/pandas/pandas/core/computation/eval.py", line 157, in _check_for_locals
    raise SyntaxError(msg)

  File "<string>", line unknown
SyntaxError: The '@' prefix is not allowed in top-level eval calls.
please refer to your variables by name without the '@' prefix.
```

In this case, you should simply refer to the variables like you would in standard Python.

```
In [51]: pd.eval("a + b")
Out[51]: 3
```

`pandas.eval()` parsers

There are two different parsers and two different engines you can use as the backend.

The default `'pandas'` parser allows a more intuitive syntax for expressing query-like operations (comparisons, conjunctions and disjunctions). In particular, the precedence of the `&` and `|` operators is made equal to the precedence of the corresponding boolean operations `and` and `or`.

For example, the above conjunction can be written without parentheses. Alternatively, you can use the `'python'` parser to enforce strict Python semantics.

```
In [52]: expr = "(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)"

In [53]: x = pd.eval(expr, parser="python")

In [54]: expr_no_parens = "df1 > 0 & df2 > 0 & df3 > 0 & df4 > 0"

In [55]: y = pd.eval(expr_no_parens, parser="pandas")

In [56]: np.all(x == y)
Out[56]: True
```

The same expression can be "anded" together with the word `and` as well:

```
In [57]: expr = "(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)"

In [58]: x = pd.eval(expr, parser="python")

In [59]: expr_with_ands = "df1 > 0 and df2 > 0 and df3 > 0 and df4 > 0"
```

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```
In [60]: y = pd.eval(expr_with_ands, parser="pandas")

In [61]: np.all(x == y)
Out[61]: True
```

The `and` and `or` operators here have the same precedence that they would in vanilla Python.

`pandas.eval()` backends

There's also the option to make *`eval()`* operate identical to plain ol' Python.

Note: Using the `'python'` engine is generally *not* useful, except for testing other evaluation engines against it. You will achieve **no** performance benefits using *`eval()`* with `engine='python'` and in fact may incur a performance hit.

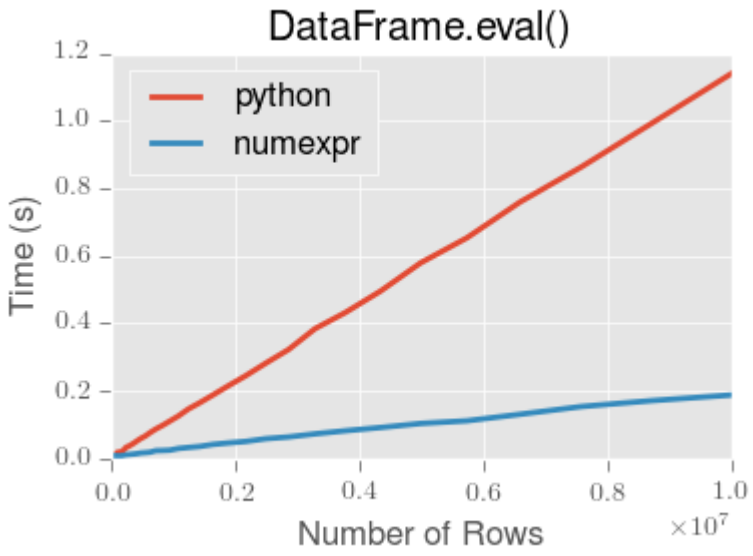
You can see this by using *`pandas.eval()`* with the `'python'` engine. It is a bit slower (not by much) than evaluating the same expression in Python

```
In [62]: %timeit df1 + df2 + df3 + df4
10.7 ms +- 147 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

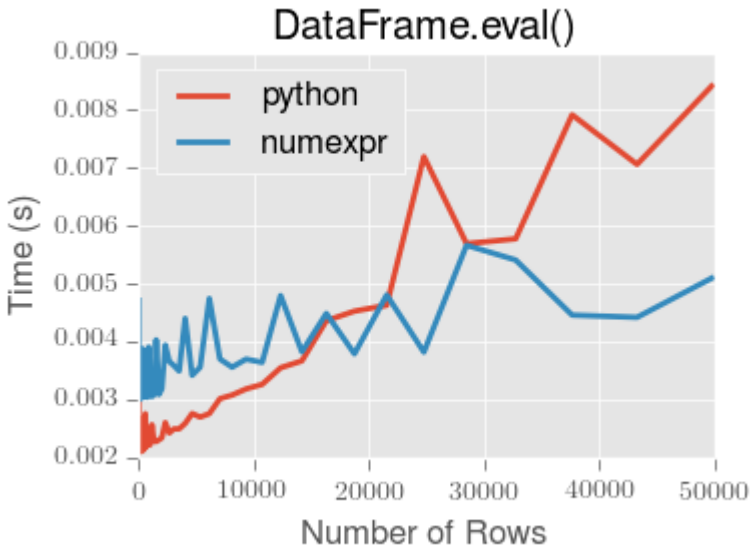
```
In [63]: %timeit pd.eval("df1 + df2 + df3 + df4", engine="python")
11.5 ms +- 128 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

`pandas.eval()` performance

`eval()` is intended to speed up certain kinds of operations. In particular, those operations involving complex expressions with large *`DataFrame`*/*`Series`* objects should see a significant performance benefit. Here is a plot showing the running time of *`pandas.eval()`* as function of the size of the frame involved in the computation. The two lines are two different engines.



Note: Operations with smallish objects (around 15k-20k rows) are faster using plain Python:



This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

Technical minutia regarding expression evaluation

Expressions that would result in an object dtype or involve datetime operations (because of `NaT`) must be evaluated in Python space. The main reason for this behavior is to maintain backwards compatibility with versions of NumPy < 1.7. In those versions of NumPy a call to `ndarray.astype(str)` will truncate any strings that are more than 60 characters in length. Second, we can't pass `object` arrays to `numexpr` thus string comparisons must be evaluated in Python space.

The upshot is that this *only* applies to object-dtype expressions. So, if you have an expression–for example

```
In [64]: df = pd.DataFrame(
   ....:     {"strings": np.repeat(list("cba"), 3), "nums": np.repeat(range(3), 3)}
   ....: )
   ....:

In [65]: df
Out[65]:
  strings  nums
0       c     0
1       c     0
2       c     0
3       b     1
4       b     1
5       b     1
6       a     2
7       a     2
8       a     2

In [66]: df.query("strings == 'a' and nums == 1")
```

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```
Out[66]:
Empty DataFrame
Columns: [strings, nums]
Index: []
```

the numeric part of the comparison (`nums == 1`) will be evaluated by `numexpr`.

In general, *`DataFrame.query()`*/*`pandas.eval()`* will evaluate the subexpressions that *can* be evaluated by `numexpr` and those that must be evaluated in Python space transparently to the user. This is done by inferring the result type of an expression from its arguments and operators.

2.24 Scaling to large datasets

pandas provides data structures for in-memory analytics, which makes using pandas to analyze datasets that are larger than memory datasets somewhat tricky. Even datasets that are a sizable fraction of memory become unwieldy, as some pandas operations need to make intermediate copies.

This document provides a few recommendations for scaling your analysis to larger datasets. It's a complement to *Enhancing performance*, which focuses on speeding up analysis for datasets that fit in memory.

But first, it's worth considering *not using pandas*. pandas isn't the right tool for all situations. If you're working with very large datasets and a tool like PostgreSQL fits your needs, then you should probably be using that. Assuming you want or need the expressiveness and power of pandas, let's carry on.

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

2.24.1 Load less data

Suppose our raw dataset on disk has many columns:

```
                     id_0    name_0       x_0       y_0  id_1    name_1       x_1  ...␣
↪ name_8       x_8       y_8  id_9   name_9       x_9       y_9
timestamp                                                                        ...
2000-01-01 00:00:00  1015   Michael -0.399453  0.095427   994     Frank -0.176842  ...␣
↪    Dan -0.315310  0.713892  1025   Victor -0.135779  0.346801
2000-01-01 00:01:00   969  Patricia  0.650773 -0.874275  1003     Laura  0.459153  ...␣
↪ Ursula  0.913244 -0.630308  1047    Wendy -0.886285  0.035852
2000-01-01 00:02:00  1016    Victor -0.721465 -0.584710  1046   Michael  0.524994  ...␣
↪    Ray -0.656593  0.692568  1064   Yvonne  0.070426  0.432047
2000-01-01 00:03:00   939     Alice -0.746004 -0.908008   996    Ingrid -0.414523  ...␣
↪  Jerry -0.958994  0.608210   978    Wendy  0.855949 -0.648988
2000-01-01 00:04:00  1017       Dan  0.919451 -0.803504  1048     Jerry -0.569235  ...␣
↪  Frank -0.577022 -0.409088   994      Bob -0.270132  0.335176
...                   ...       ...       ...       ...   ...      ...       ...  ...␣
↪    ...       ...       ...   ...       ...       ...       ...
2000-12-30 23:56:00   999       Tim  0.162578  0.512817   973    Kevin -0.403352  ...␣
↪    Tim -0.380415  0.008097  1041  Charlie  0.191477 -0.599519
2000-12-30 23:57:00   970     Laura -0.433586 -0.600289   958   Oliver -0.966577  ...␣
↪  Zelda  0.971274  0.402032  1038   Ursula  0.574016 -0.930992
2000-12-30 23:58:00  1065     Edith  0.232211 -0.454540   971      Tim  0.158484  ...␣
↪  Alice -0.222079 -0.919274  1022      Dan  0.031345 -0.657755
```

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```
2000-12-30 23:59:00  1019    Ingrid  0.322208 -0.615974   981    Hannah  0.607517  ...␣
↪  Sarah -0.424440 -0.117274   990   George -0.375530  0.563312
2000-12-31 00:00:00   937    Ursula -0.906523  0.943178  1018     Alice -0.564513  ...␣
↪  Jerry  0.236837  0.807650   985   Oliver  0.777642  0.783392

[525601 rows x 40 columns]
```

To load the columns we want, we have two options. Option 1 loads in all the data and then filters to what we need.

```
In [3]: columns = ["id_0", "name_0", "x_0", "y_0"]

In [4]: pd.read_parquet("timeseries_wide.parquet")[columns]
Out[4]:
                     id_0    name_0       x_0       y_0
timestamp
2000-01-01 00:00:00  1015   Michael -0.399453  0.095427
2000-01-01 00:01:00   969  Patricia  0.650773 -0.874275
2000-01-01 00:02:00  1016    Victor -0.721465 -0.584710
2000-01-01 00:03:00   939     Alice -0.746004 -0.908008
2000-01-01 00:04:00  1017       Dan  0.919451 -0.803504
...                   ...       ...       ...       ...
2000-12-30 23:56:00   999       Tim  0.162578  0.512817
2000-12-30 23:57:00   970     Laura -0.433586 -0.600289
2000-12-30 23:58:00  1065     Edith  0.232211 -0.454540
2000-12-30 23:59:00  1019    Ingrid  0.322208 -0.615974
2000-12-31 00:00:00   937    Ursula -0.906523  0.943178

[525601 rows x 4 columns]
```

Option 2 only loads the columns we request.

```
In [5]: pd.read_parquet("timeseries_wide.parquet", columns=columns)
Out[5]:
                     id_0    name_0       x_0       y_0
timestamp
2000-01-01 00:00:00  1015   Michael -0.399453  0.095427
2000-01-01 00:01:00   969  Patricia  0.650773 -0.874275
2000-01-01 00:02:00  1016    Victor -0.721465 -0.584710
2000-01-01 00:03:00   939     Alice -0.746004 -0.908008
2000-01-01 00:04:00  1017       Dan  0.919451 -0.803504
...                   ...       ...       ...       ...
2000-12-30 23:56:00   999       Tim  0.162578  0.512817
2000-12-30 23:57:00   970     Laura -0.433586 -0.600289
2000-12-30 23:58:00  1065     Edith  0.232211 -0.454540
2000-12-30 23:59:00  1019    Ingrid  0.322208 -0.615974
2000-12-31 00:00:00   937    Ursula -0.906523  0.943178

[525601 rows x 4 columns]
```

If we were to measure the memory usage of the two calls, we'd see that specifying `columns` uses about 1/10th the memory in this case.

With *`pandas.read_csv()`*, you can specify `usecols` to limit the columns read into memory. Not all file formats that can be read by pandas provide an option to read a subset of columns.

2.24.2 Use efficient datatypes

The default pandas data types are not the most memory efficient. This is especially true for text data columns with relatively few unique values (commonly referred to as "low-cardinality" data). By using more efficient data types, you can store larger datasets in memory.

```
In [6]: ts = pd.read_parquet("timeseries.parquet")

In [7]: ts
Out[7]:
                        id      name         x         y
timestamp
2000-01-01 00:00:00   1029   Michael  0.278837  0.247932
2000-01-01 00:00:30   1010  Patricia  0.077144  0.490260
2000-01-01 00:01:00   1001    Victor  0.214525  0.258635
2000-01-01 00:01:30   1018     Alice -0.646866  0.822104
2000-01-01 00:02:00    991       Dan  0.902389  0.466665
...                    ...       ...       ...       ...
2000-12-30 23:58:00    992     Sarah  0.721155  0.944118
2000-12-30 23:58:30   1007    Ursula  0.409277  0.133227
2000-12-30 23:59:00   1009    Hannah -0.452802  0.184318
2000-12-30 23:59:30    978     Kevin -0.904728 -0.179146
2000-12-31 00:00:00    973    Ingrid -0.370763 -0.794667

[1051201 rows x 4 columns]
```

Now, let's inspect the data types and memory usage to see where we should focus our attention.

```
In [8]: ts.dtypes
Out[8]:
id        int64
name     object
x       float64
y       float64
dtype: object
```

```
In [9]: ts.memory_usage(deep=True)  # memory usage in bytes
Out[9]:
Index     8409608
id        8409608
name     65537768
x         8409608
y         8409608
dtype: int64
```

The `name` column is taking up much more memory than any other. It has just a few unique values, so it's a good candidate for converting to a `Categorical`. With a Categorical, we store each unique name once and use space-efficient integers to know which specific name is used in each row.

```
In [10]: ts2 = ts.copy()

In [11]: ts2["name"] = ts2["name"].astype("category")

In [12]: ts2.memory_usage(deep=True)
Out[12]:
Index    8409608
id       8409608
```

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```
name     1053894
x        8409608
y        8409608
dtype: int64
```

We can go a bit further and downcast the numeric columns to their smallest types using *pandas.to_numeric()*.

```
In [13]: ts2["id"] = pd.to_numeric(ts2["id"], downcast="unsigned")

In [14]: ts2[["x", "y"]] = ts2[["x", "y"]].apply(pd.to_numeric, downcast="float")

In [15]: ts2.dtypes
Out[15]:
id         uint16
name     category
x         float32
y         float32
dtype: object
```

```
In [16]: ts2.memory_usage(deep=True)
Out[16]:
Index    8409608
id       2102402
name     1053894
x        4204804
y        4204804
dtype: int64
```

```
In [17]: reduction = ts2.memory_usage(deep=True).sum() / ts.memory_usage(deep=True).
↪sum()

In [18]: print(f"{reduction:0.2f}")
0.20
```

In all, we've reduced the in-memory footprint of this dataset to 1/5 of its original size.

See *Categorical data* for more on `Categorical` and *dtypes* for an overview of all of pandas' dtypes.

2.24.3 Use chunking

Some workloads can be achieved with chunking: splitting a large problem like "convert this directory of CSVs to parquet" into a bunch of small problems ("convert this individual CSV file into a Parquet file. Now repeat that for each file in this directory."). As long as each chunk fits in memory, you can work with datasets that are much larger than memory.

Note: Chunking works well when the operation you're performing requires zero or minimal coordination between chunks. For more complicated workflows, you're better off *using another library*.

Suppose we have an even larger "logical dataset" on disk that's a directory of parquet files. Each file in the directory represents a different year of the entire dataset.

```
data
└── timeseries
```

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```
    ├── ts-00.parquet
    ├── ts-01.parquet
    ├── ts-02.parquet
    ├── ts-03.parquet
    ├── ts-04.parquet
    ├── ts-05.parquet
    ├── ts-06.parquet
    ├── ts-07.parquet
    ├── ts-08.parquet
    ├── ts-09.parquet
    ├── ts-10.parquet
    └── ts-11.parquet
```

Now we'll implement an out-of-core `value_counts`. The peak memory usage of this workflow is the single largest chunk, plus a small series storing the unique value counts up to this point. As long as each individual file fits in memory, this will work for arbitrary-sized datasets.

```
In [19]: %%time
   ....: files = pathlib.Path("data/timeseries/").glob("ts*.parquet")
   ....: counts = pd.Series(dtype=int)
   ....: for path in files:
   ....:     df = pd.read_parquet(path)
   ....:     counts = counts.add(df["name"].value_counts(), fill_value=0)
   ....: counts.astype(int)
   ....:
CPU times: user 718 ms, sys: 76.9 ms, total: 795 ms
Wall time: 596 ms
Out[19]:
Alice      229802
Bob        229211
Charlie    229303
Dan        230621
Edith      230349
            ...
Victor     230502
Wendy      230038
Xavier     229553
Yvonne     228766
Zelda      229909
Length: 26, dtype: int64
```

Some readers, like *pandas.read_csv()*, offer parameters to control the `chunksize` when reading a single file.

Manually chunking is an OK option for workflows that don't require too sophisticated of operations. Some operations, like `groupby`, are much harder to do chunkwise. In these cases, you may be better switching to a different library that implements these out-of-core algorithms for you.

2.24.4 Use other libraries

pandas is just one library offering a DataFrame API. Because of its popularity, pandas' API has become something of a standard that other libraries implement. The pandas documentation maintains a list of libraries implementing a DataFrame API in our ecosystem page.

For example, Dask, a parallel computing library, has dask.dataframe, a pandas-like API for working with larger than memory datasets in parallel. Dask can use multiple threads or processes on a single machine, or a cluster of machines to process data in parallel.

We'll import `dask.dataframe` and notice that the API feels similar to pandas. We can use Dask's `read_parquet` function, but provide a globstring of files to read in.

```
In [20]: import dask.dataframe as dd

In [21]: ddf = dd.read_parquet("data/timeseries/ts*.parquet", engine="pyarrow")

In [22]: ddf
Out[22]:
Dask DataFrame Structure:
                   id    name        x        y
npartitions=12
                int64  object  float64  float64
                  ...     ...      ...      ...
...               ...     ...      ...      ...
                  ...     ...      ...      ...
                  ...     ...      ...      ...
Dask Name: read-parquet, 12 tasks
```

Inspecting the `ddf` object, we see a few things

- There are familiar attributes like `.columns` and `.dtypes`
- There are familiar methods like `.groupby`, `.sum`, etc.
- There are new attributes like `.npartitions` and `.divisions`

The partitions and divisions are how Dask parallelizes computation. A **Dask** DataFrame is made up of many pandas DataFrames. A single method call on a Dask DataFrame ends up making many pandas method calls, and Dask knows how to coordinate everything to get the result.

```
In [23]: ddf.columns
Out[23]: Index(['id', 'name', 'x', 'y'], dtype='object')

In [24]: ddf.dtypes
Out[24]:
id        int64
name     object
x       float64
y       float64
dtype: object

In [25]: ddf.npartitions
Out[25]: 12
```

One major difference: the `dask.dataframe` API is *lazy*. If you look at the repr above, you'll notice that the values aren't actually printed out; just the column names and dtypes. That's because Dask hasn't actually read the data yet. Rather than executing immediately, doing operations build up a **task graph**.

```
In [26]: ddf
Out[26]:
Dask DataFrame Structure:
                   id    name        x        y
npartitions=12
                int64  object  float64  float64
                  ...     ...      ...      ...
...               ...     ...      ...      ...
                  ...     ...      ...      ...
                  ...     ...      ...      ...
Dask Name: read-parquet, 12 tasks

In [27]: ddf["name"]
Out[27]:
Dask Series Structure:
npartitions=12
    object
       ...
     ...
       ...
       ...
Name: name, dtype: object
Dask Name: getitem, 24 tasks

In [28]: ddf["name"].value_counts()
Out[28]:
Dask Series Structure:
npartitions=1
    int64
      ...
Name: name, dtype: int64
Dask Name: value-counts-agg, 39 tasks
```

Each of these calls is instant because the result isn't being computed yet. We're just building up a list of computation to do when someone needs the result. Dask knows that the return type of a `pandas.Series.value_counts` is a pandas Series with a certain dtype and a certain name. So the Dask version returns a Dask Series with the same dtype and the same name.

To get the actual result you can call `.compute()`.

```
In [29]: %time ddf["name"].value_counts().compute()
CPU times: user 852 ms, sys: 266 ms, total: 1.12 s
Wall time: 587 ms
Out[29]:
Laura      230906
Ingrid     230838
Kevin      230698
Dan        230621
Frank      230595
            ...
Ray        229603
Xavier     229553
Charlie    229303
Bob        229211
Yvonne     228766
Name: name, Length: 26, dtype: int64
```

At that point, you get back the same thing you'd get with pandas, in this case a concrete pandas Series with the count

of each `name`.

Calling `.compute` causes the full task graph to be executed. This includes reading the data, selecting the columns, and doing the `value_counts`. The execution is done *in parallel* where possible, and Dask tries to keep the overall memory footprint small. You can work with datasets that are much larger than memory, as long as each partition (a regular pandas DataFrame) fits in memory.

By default, `dask.dataframe` operations use a threadpool to do operations in parallel. We can also connect to a cluster to distribute the work on many machines. In this case we'll connect to a local "cluster" made up of several processes on this single machine.

```
>>> from dask.distributed import Client, LocalCluster

>>> cluster = LocalCluster()
>>> client = Client(cluster)
>>> client
<Client: 'tcp://127.0.0.1:53349' processes=4 threads=8, memory=17.18 GB>
```

Once this `client` is created, all of Dask's computation will take place on the cluster (which is just processes in this case).

Dask implements the most used parts of the pandas API. For example, we can do a familiar groupby aggregation.

```
In [30]: %time ddf.groupby("name")[["x", "y"]].mean().compute().head()
CPU times: user 1.71 s, sys: 361 ms, total: 2.08 s
Wall time: 799 ms
Out[30]:
                x         y
name
Alice    0.000086 -0.001170
Bob     -0.000843 -0.000799
Charlie  0.000564 -0.000038
Dan      0.000584  0.000818
Edith   -0.000116 -0.000044
```

The grouping and aggregation is done out-of-core and in parallel.

When Dask knows the `divisions` of a dataset, certain optimizations are possible. When reading parquet datasets written by dask, the divisions will be known automatically. In this case, since we created the parquet files manually, we need to supply the divisions manually.

```
In [31]: N = 12

In [32]: starts = [f"20{i:>02d}-01-01" for i in range(N)]

In [33]: ends = [f"20{i:>02d}-12-13" for i in range(N)]

In [34]: divisions = tuple(pd.to_datetime(starts)) + (pd.Timestamp(ends[-1]),)

In [35]: ddf.divisions = divisions

In [36]: ddf
Out[36]:
Dask DataFrame Structure:
                   id    name        x        y
npartitions=12
2000-01-01      int64  object  float64  float64
2001-01-01        ...     ...      ...      ...
...               ...     ...      ...      ...
```

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```
2011-01-01        ...      ...      ...      ...
2011-12-13        ...      ...      ...      ...
Dask Name: read-parquet, 12 tasks
```

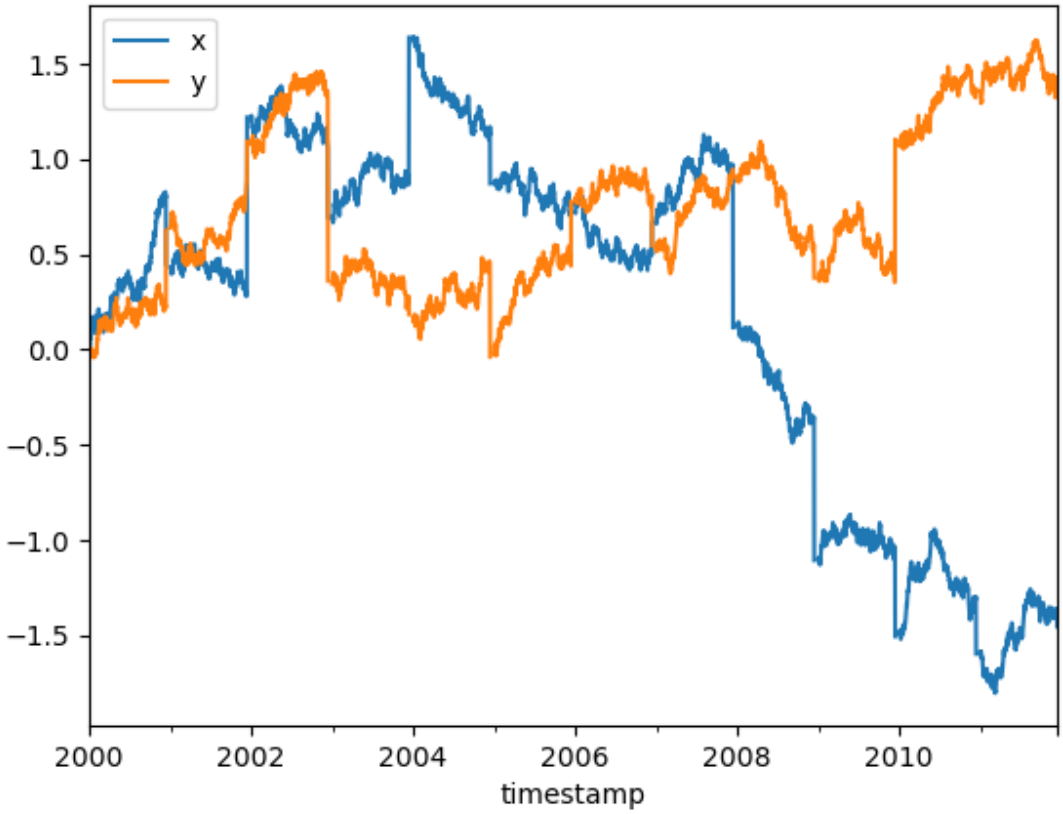
Now we can do things like fast random access with `.loc`.

```
In [37]: ddf.loc["2002-01-01 12:01":"2002-01-01 12:05"].compute()
Out[37]:
                     id    name         x         y
timestamp
2002-01-01 12:01:00   983   Laura  0.243985 -0.079392
2002-01-01 12:02:00  1001   Laura -0.523119 -0.226026
2002-01-01 12:03:00  1059  Oliver  0.612886  0.405680
2002-01-01 12:04:00   993   Kevin  0.451977  0.332947
2002-01-01 12:05:00  1014  Yvonne -0.948681  0.361748
```

Dask knows to just look in the 3rd partition for selecting values in 2002. It doesn't need to look at any other data.

Many workflows involve a large amount of data and processing it in a way that reduces the size to something that fits in memory. In this case, we'll resample to daily frequency and take the mean. Once we've taken the mean, we know the results will fit in memory, so we can safely call `compute` without running out of memory. At that point it's just a regular pandas object.

```
In [38]: ddf[["x", "y"]].resample("1D").mean().cumsum().compute().plot()
Out[38]: <AxesSubplot:xlabel='timestamp'>
```



These Dask examples have all be done using multiple processes on a single machine. Dask can be deployed on a cluster to scale up to even larger datasets.

You see more dask examples at https://examples.dask.org.

2.25 Sparse data structures

pandas provides data structures for efficiently storing sparse data. These are not necessarily sparse in the typical "mostly 0". Rather, you can view these objects as being "compressed" where any data matching a specific value (`NaN` / missing value, though any value can be chosen, including 0) is omitted. The compressed values are not actually stored in the array.

```
In [1]: arr = np.random.randn(10)

In [2]: arr[2:-2] = np.nan

In [3]: ts = pd.Series(pd.arrays.SparseArray(arr))

In [4]: ts
Out[4]:
0    0.469112
1   -0.282863
2         NaN
```

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```
3         NaN
4         NaN
5         NaN
6         NaN
7         NaN
8   -0.861849
9   -2.104569
dtype: Sparse[float64, nan]
```

Notice the dtype, `Sparse[float64, nan]`. The `nan` means that elements in the array that are `nan` aren't actually stored, only the non-`nan` elements are. Those non-`nan` elements have a `float64` dtype.

The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA `DataFrame`:

```
In [5]: df = pd.DataFrame(np.random.randn(10000, 4))

In [6]: df.iloc[:9998] = np.nan

In [7]: sdf = df.astype(pd.SparseDtype("float", np.nan))

In [8]: sdf.head()
Out[8]:
     0   1   2   3
0 NaN NaN NaN NaN
1 NaN NaN NaN NaN
2 NaN NaN NaN NaN
3 NaN NaN NaN NaN
4 NaN NaN NaN NaN

In [9]: sdf.dtypes
Out[9]:
0    Sparse[float64, nan]
1    Sparse[float64, nan]
2    Sparse[float64, nan]
3    Sparse[float64, nan]
dtype: object

In [10]: sdf.sparse.density
Out[10]: 0.0002
```

As you can see, the density (% of values that have not been "compressed") is extremely low. This sparse object takes up much less memory on disk (pickled) and in the Python interpreter.

```
In [11]: 'dense : {:0.2f} bytes'.format(df.memory_usage().sum() / 1e3)
Out[11]: 'dense : 320.13 bytes'

In [12]: 'sparse: {:0.2f} bytes'.format(sdf.memory_usage().sum() / 1e3)
Out[12]: 'sparse: 0.22 bytes'
```

Functionally, their behavior should be nearly identical to their dense counterparts.

2.25.1 SparseArray

arrays.SparseArray is a *ExtensionArray* for storing an array of sparse values (see *dtypes* for more on extension arrays). It is a 1-dimensional ndarray-like object storing only values distinct from the `fill_value`:

```
In [13]: arr = np.random.randn(10)

In [14]: arr[2:5] = np.nan

In [15]: arr[7:8] = np.nan

In [16]: sparr = pd.arrays.SparseArray(arr)

In [17]: sparr
Out[17]:
[-1.9556635297215477, -1.6588664275960427, nan, nan, nan, 1.1589328886422277, 0.
↪14529711373305043, nan, 0.6060271905134522, 1.3342113401317768]
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9], dtype=int32)
```

A sparse array can be converted to a regular (dense) ndarray with `numpy.asarray()`

```
In [18]: np.asarray(sparr)
Out[18]:
array([-1.9557, -1.6589,     nan,     nan,     nan,  1.1589,  0.1453,
           nan,  0.606 ,  1.3342])
```

2.25.2 SparseDtype

The `SparseArray.dtype` property stores two pieces of information

1. The dtype of the non-sparse values
2. The scalar fill value

```
In [19]: sparr.dtype
Out[19]: Sparse[float64, nan]
```

A *SparseDtype* may be constructed by passing only a dtype

```
In [20]: pd.SparseDtype(np.dtype('datetime64[ns]'))
Out[20]: Sparse[datetime64[ns], NaT]
```

in which case a default fill value will be used (for NumPy dtypes this is often the "missing" value for that dtype). To override this default an explicit fill value may be passed instead

```
In [21]: pd.SparseDtype(np.dtype('datetime64[ns]'),
   ....:                fill_value=pd.Timestamp('2017-01-01'))
   ....:
Out[21]: Sparse[datetime64[ns], Timestamp('2017-01-01 00:00:00')]
```

Finally, the string alias `'Sparse[dtype]'` may be used to specify a sparse dtype in many places

```
In [22]: pd.array([1, 0, 0, 2], dtype='Sparse[int]')
Out[22]:
```

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```
[1, 0, 0, 2]
Fill: 0
IntIndex
Indices: array([0, 3], dtype=int32)
```

2.25.3 Sparse accessor

New in version 0.24.0.

pandas provides a `.sparse` accessor, similar to `.str` for string data, `.cat` for categorical data, and `.dt` for datetime-like data. This namespace provides attributes and methods that are specific to sparse data.

```
In [23]: s = pd.Series([0, 0, 1, 2], dtype="Sparse[int]")

In [24]: s.sparse.density
Out[24]: 0.5

In [25]: s.sparse.fill_value
Out[25]: 0
```

This accessor is available only on data with `SparseDtype`, and on the *`Series`* class itself for creating a Series with sparse data from a scipy COO matrix with.

New in version 0.25.0.

A `.sparse` accessor has been added for *`DataFrame`* as well. See *Sparse accessor* for more.

2.25.4 Sparse calculation

You can apply NumPy ufuncs to `SparseArray` and get a `SparseArray` as a result.

```
In [26]: arr = pd.arrays.SparseArray([1., np.nan, np.nan, -2., np.nan])

In [27]: np.abs(arr)
Out[27]:
[1.0, nan, nan, 2.0, nan]
Fill: nan
IntIndex
Indices: array([0, 3], dtype=int32)
```

The *ufunc* is also applied to `fill_value`. This is needed to get the correct dense result.

```
In [28]: arr = pd.arrays.SparseArray([1., -1, -1, -2., -1], fill_value=-1)

In [29]: np.abs(arr)
Out[29]:
[1.0, 1, 1, 2.0, 1]
Fill: 1
IntIndex
Indices: array([0, 3], dtype=int32)

In [30]: np.abs(arr).to_dense()
Out[30]: array([1., 1., 1., 2., 1.])
```

2.25.5 Migrating

Note: `SparseSeries` and `SparseDataFrame` were removed in pandas 1.0.0. This migration guide is present to aid in migrating from previous versions.

In older versions of pandas, the `SparseSeries` and `SparseDataFrame` classes (documented below) were the preferred way to work with sparse data. With the advent of extension arrays, these subclasses are no longer needed. Their purpose is better served by using a regular Series or DataFrame with sparse values instead.

Note: There's no performance or memory penalty to using a Series or DataFrame with sparse values, rather than a SparseSeries or SparseDataFrame.

This section provides some guidance on migrating your code to the new style. As a reminder, you can use the Python warnings module to control warnings. But we recommend modifying your code, rather than ignoring the warning.

Construction

From an array-like, use the regular *Series* or *DataFrame* constructors with `SparseArray` values.

```
# Previous way
>>> pd.SparseDataFrame({"A": [0, 1]})
```

```
# New way
In [31]: pd.DataFrame({"A": pd.arrays.SparseArray([0, 1])})
Out[31]:
   A
0  0
1  1
```

From a SciPy sparse matrix, use *DataFrame.sparse.from_spmatrix()*,

```
# Previous way
>>> from scipy import sparse
>>> mat = sparse.eye(3)
>>> df = pd.SparseDataFrame(mat, columns=['A', 'B', 'C'])
```

```
# New way
In [32]: from scipy import sparse

In [33]: mat = sparse.eye(3)

In [34]: df = pd.DataFrame.sparse.from_spmatrix(mat, columns=['A', 'B', 'C'])

In [35]: df.dtypes
Out[35]:
A    Sparse[float64, 0]
B    Sparse[float64, 0]
C    Sparse[float64, 0]
dtype: object
```

Conversion

From sparse to dense, use the `.sparse` accessors

```
In [36]: df.sparse.to_dense()
Out[36]:
     A    B    C
0  1.0  0.0  0.0
1  0.0  1.0  0.0
2  0.0  0.0  1.0

In [37]: df.sparse.to_coo()
Out[37]:
<3x3 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in COOrdinate format>
```

From dense to sparse, use *DataFrame.astype()* with a *SparseDtype*.

```
In [38]: dense = pd.DataFrame({"A": [1, 0, 0, 1]})

In [39]: dtype = pd.SparseDtype(int, fill_value=0)

In [40]: dense.astype(dtype)
Out[40]:
   A
0  1
1  0
2  0
3  1
```

Sparse Properties

Sparse-specific properties, like `density`, are available on the `.sparse` accessor.

```
In [41]: df.sparse.density
Out[41]: 0.3333333333333333
```

General differences

In a `SparseDataFrame`, *all* columns were sparse. A *DataFrame* can have a mixture of sparse and dense columns. As a consequence, assigning new columns to a `DataFrame` with sparse values will not automatically convert the input to be sparse.

```
# Previous Way
>>> df = pd.SparseDataFrame({"A": [0, 1]})
>>> df['B'] = [0, 0]  # implicitly becomes Sparse
>>> df['B'].dtype
Sparse[int64, nan]
```

Instead, you'll need to ensure that the values being assigned are sparse

```
In [42]: df = pd.DataFrame({"A": pd.arrays.SparseArray([0, 1])})

In [43]: df['B'] = [0, 0]  # remains dense

In [44]: df['B'].dtype
Out[44]: dtype('int64')

In [45]: df['B'] = pd.arrays.SparseArray([0, 0])

In [46]: df['B'].dtype
Out[46]: Sparse[int64, 0]
```

The `SparseDataFrame.default_kind` and `SparseDataFrame.default_fill_value` attributes have no replacement.

2.25.6 Interaction with scipy.sparse

Use *`DataFrame.sparse.from_spmatrix()`* to create a `DataFrame` with sparse values from a sparse matrix.

New in version 0.25.0.

```
In [47]: from scipy.sparse import csr_matrix

In [48]: arr = np.random.random(size=(1000, 5))

In [49]: arr[arr < .9] = 0

In [50]: sp_arr = csr_matrix(arr)

In [51]: sp_arr
Out[51]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
        with 517 stored elements in Compressed Sparse Row format>

In [52]: sdf = pd.DataFrame.sparse.from_spmatrix(sp_arr)

In [53]: sdf.head()
Out[53]:
          0    1    2         3    4
0  0.956380  0.0  0.0  0.000000  0.0
1  0.000000  0.0  0.0  0.000000  0.0
2  0.000000  0.0  0.0  0.000000  0.0
3  0.000000  0.0  0.0  0.000000  0.0
4  0.999552  0.0  0.0  0.956153  0.0

In [54]: sdf.dtypes
Out[54]:
0    Sparse[float64, 0]
1    Sparse[float64, 0]
2    Sparse[float64, 0]
3    Sparse[float64, 0]
4    Sparse[float64, 0]
dtype: object
```

All sparse formats are supported, but matrices that are not in `COOrdinate` format will be converted, copying data as needed. To convert back to sparse SciPy matrix in COO format, you can use the *`DataFrame.sparse.to_coo()`* method:

```
In [55]: sdf.sparse.to_coo()
Out[55]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
        with 517 stored elements in COOrdinate format>
```

meth:*Series.sparse.to_coo* is implemented for transforming a `Series` with sparse values indexed by a *`MultiIndex`* to a `scipy.sparse.coo_matrix`.

The method requires a `MultiIndex` with two or more levels.

```
In [56]: s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])

In [57]: s.index = pd.MultiIndex.from_tuples(
   ....:     [
   ....:         (1, 2, "a", 0),
   ....:         (1, 2, "a", 1),
   ....:         (1, 1, "b", 0),
   ....:         (1, 1, "b", 1),
   ....:         (2, 1, "b", 0),
   ....:         (2, 1, "b", 1),
   ....:     ],
   ....:     names=["A", "B", "C", "D"],
   ....: )
   ....:

In [58]: ss = s.astype('Sparse')

In [59]: ss
Out[59]:
A  B  C  D
1  2  a  0    3.0
          1    NaN
   1  b  0    1.0
          1    3.0
2  1  b  0    NaN
          1    NaN
dtype: Sparse[float64, nan]
```

In the example below, we transform the `Series` to a sparse representation of a 2-d array by specifying that the first and second `MultiIndex` levels define labels for the rows and the third and fourth levels define labels for the columns. We also specify that the column and row labels should be sorted in the final sparse representation.

```
In [60]: A, rows, columns = ss.sparse.to_coo(
   ....:     row_levels=["A", "B"], column_levels=["C", "D"], sort_labels=True
   ....: )
   ....:

In [61]: A
Out[61]:
<3x4 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in COOrdinate format>

In [62]: A.todense()
Out[62]:
matrix([[0., 0., 1., 3.],
        [3., 0., 0., 0.],
        [0., 0., 0., 0.]])

In [63]: rows
Out[63]: [(1, 1), (1, 2), (2, 1)]

In [64]: columns
Out[64]: [('a', 0), ('a', 1), ('b', 0), ('b', 1)]
```

Specifying different row and column labels (and not sorting them) yields a different sparse matrix:

```
In [65]: A, rows, columns = ss.sparse.to_coo(
```

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```
   ....:     row_levels=["A", "B", "C"], column_levels=["D"], sort_labels=False
   ....: )
   ....:

In [66]: A
Out[66]:
<3x2 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in COOrdinate format>

In [67]: A.todense()
Out[67]:
matrix([[3., 0.],
        [1., 3.],
        [0., 0.]])

In [68]: rows
Out[68]: [(1, 2, 'a'), (1, 1, 'b'), (2, 1, 'b')]

In [69]: columns
Out[69]: [0, 1]
```

A convenience method *`Series.sparse.from_coo()`* is implemented for creating a `Series` with sparse values from a `scipy.sparse.coo_matrix`.

```
In [70]: from scipy import sparse

In [71]: A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])), shape=(3,␣
↪4))

In [72]: A
Out[72]:
<3x4 sparse matrix of type '<class 'numpy.float64'>'
        with 3 stored elements in COOrdinate format>

In [73]: A.todense()
Out[73]:
matrix([[0., 0., 1., 2.],
        [3., 0., 0., 0.],
        [0., 0., 0., 0.]])
```

The default behaviour (with `dense_index=False`) simply returns a `Series` containing only the non-null entries.

```
In [74]: ss = pd.Series.sparse.from_coo(A)

In [75]: ss
Out[75]:
0  2    1.0
   3    2.0
1  0    3.0
dtype: Sparse[float64, nan]
```

Specifying `dense_index=True` will result in an index that is the Cartesian product of the row and columns coordinates of the matrix. Note that this will consume a significant amount of memory (relative to `dense_index=False`) if the sparse matrix is large (and sparse) enough.

```
In [76]: ss_dense = pd.Series.sparse.from_coo(A, dense_index=True)
```

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```
In [77]: ss_dense
Out[77]:
0  0    NaN
   1    NaN
   2    1.0
   3    2.0
1  0    3.0
   1    NaN
   2    NaN
   3    NaN
2  0    NaN
   1    NaN
   2    NaN
   3    NaN
dtype: Sparse[float64, nan]
```

2.26 Frequently Asked Questions (FAQ)

2.26.1 DataFrame memory usage

The memory usage of a `DataFrame` (including the index) is shown when calling the *`info()`*. A configuration option, `display.memory_usage` (see *the list of options*), specifies if the `DataFrame`'s memory usage will be displayed when invoking the `df.info()` method.

For example, the memory usage of the `DataFrame` below is shown when calling *`info()`*:

```
In [1]: dtypes = [
   ...:     "int64",
   ...:     "float64",
   ...:     "datetime64[ns]",
   ...:     "timedelta64[ns]",
   ...:     "complex128",
   ...:     "object",
   ...:     "bool",
   ...: ]
   ...:

In [2]: n = 5000

In [3]: data = {t: np.random.randint(100, size=n).astype(t) for t in dtypes}

In [4]: df = pd.DataFrame(data)

In [5]: df["categorical"] = df["object"].astype("category")

In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   int64            5000 non-null   int64
 1   float64          5000 non-null   float64
```

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```
 2   datetime64[ns]   5000 non-null   datetime64[ns]
 3   timedelta64[ns]  5000 non-null   timedelta64[ns]
 4   complex128       5000 non-null   complex128
 5   object           5000 non-null   object
 6   bool             5000 non-null   bool
 7   categorical      5000 non-null   category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1),␣
↪object(1), timedelta64[ns](1)
memory usage: 288.2+ KB
```

The + symbol indicates that the true memory usage could be higher, because pandas does not count the memory used by values in columns with `dtype=object`.

Passing `memory_usage='deep'` will enable a more accurate memory usage report, accounting for the full usage of the contained objects. This is optional as it can be expensive to do this deeper introspection.

```
In [7]: df.info(memory_usage="deep")
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   int64            5000 non-null   int64
 1   float64          5000 non-null   float64
 2   datetime64[ns]   5000 non-null   datetime64[ns]
 3   timedelta64[ns]  5000 non-null   timedelta64[ns]
 4   complex128       5000 non-null   complex128
 5   object           5000 non-null   object
 6   bool             5000 non-null   bool
 7   categorical      5000 non-null   category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1),␣
↪object(1), timedelta64[ns](1)
memory usage: 424.7 KB
```

By default the display option is set to `True` but can be explicitly overridden by passing the `memory_usage` argument when invoking `df.info()`.

The memory usage of each column can be found by calling the *`memory_usage()`* method. This returns a `Series` with an index represented by column names and memory usage of each column shown in bytes. For the `DataFrame` above, the memory usage of each column and the total memory usage can be found with the `memory_usage` method:

```
In [8]: df.memory_usage()
Out[8]:
Index               128
int64             40000
float64           40000
datetime64[ns]    40000
timedelta64[ns]   40000
complex128        80000
object            40000
bool               5000
categorical        9968
dtype: int64

# total memory usage of dataframe
In [9]: df.memory_usage().sum()
Out[9]: 295096
```

By default the memory usage of the DataFrame's index is shown in the returned Series, the memory usage of the index can be suppressed by passing the index=False argument:

```
In [10]: df.memory_usage(index=False)
Out[10]:
int64               40000
float64             40000
datetime64[ns]      40000
timedelta64[ns]     40000
complex128          80000
object              40000
bool                 5000
categorical          9968
dtype: int64
```

The memory usage displayed by the *info()* method utilizes the *memory_usage()* method to determine the memory usage of a DataFrame while also formatting the output in human-readable units (base-2 representation; i.e. 1KB = 1024 bytes).

See also *Categorical Memory Usage*.

2.26.2 Using if/truth statements with pandas

pandas follows the NumPy convention of raising an error when you try to convert something to a bool. This happens in an if-statement or when using the boolean operations: and, or, and not. It is not clear what the result of the following code should be:

```
>>> if pd.Series([False, True, False]):
...     pass
```

Should it be True because it's not zero-length, or False because there are False values? It is unclear, so instead, pandas raises a ValueError:

```
>>> if pd.Series([False, True, False]):
...     print("I was true")
Traceback
    ...
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

You need to explicitly choose what you want to do with the DataFrame, e.g. use *any()*, *all()* or *empty()*. Alternatively, you might want to compare if the pandas object is None:

```
>>> if pd.Series([False, True, False]) is not None:
...     print("I was not None")
I was not None
```

Below is how to check if any of the values are True:

```
>>> if pd.Series([False, True, False]).any():
...     print("I am any")
I am any
```

To evaluate single-element pandas objects in a boolean context, use the method *bool()*:

```
In [11]: pd.Series([True]).bool()
Out[11]: True
```

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```
In [12]: pd.Series([False]).bool()
Out[12]: False

In [13]: pd.DataFrame([[True]]).bool()
Out[13]: True

In [14]: pd.DataFrame([[False]]).bool()
Out[14]: False
```

Bitwise boolean

Bitwise boolean operators like == and != return a boolean `Series`, which is almost always what you want anyways.

```
>>> s = pd.Series(range(5))
>>> s == 4
0    False
1    False
2    False
3    False
4     True
dtype: bool
```

See *boolean comparisons* for more examples.

Using the `in` operator

Using the Python `in` operator on a `Series` tests for membership in the index, not membership among the values.

```
In [15]: s = pd.Series(range(5), index=list("abcde"))

In [16]: 2 in s
Out[16]: False

In [17]: 'b' in s
Out[17]: True
```

If this behavior is surprising, keep in mind that using `in` on a Python dictionary tests keys, not values, and `Series` are dict-like. To test for membership in the values, use the method *`isin()`*:

```
In [18]: s.isin([2])
Out[18]:
a    False
b    False
c     True
d    False
e    False
dtype: bool

In [19]: s.isin([2]).any()
Out[19]: True
```

For `DataFrames`, likewise, `in` applies to the column axis, testing for membership in the list of column names.

2.26.3 NaN, Integer NA values and NA type promotions

Choice of NA representation

For lack of NA (missing) support from the ground up in NumPy and Python in general, we were given the difficult choice between either:

- A *masked array* solution: an array of data and an array of boolean values indicating whether a value is there or is missing.
- Using a special sentinel value, bit pattern, or set of sentinel values to denote NA across the dtypes.

For many reasons we chose the latter. After years of production use it has proven, at least in my opinion, to be the best decision given the state of affairs in NumPy and Python in general. The special value NaN (Not-A-Number) is used everywhere as the NA value, and there are API functions isna and notna which can be used across the dtypes to detect NA values.

However, it comes with it a couple of trade-offs which I most certainly have not ignored.

Support for integer NA

In the absence of high performance NA support being built into NumPy from the ground up, the primary casualty is the ability to represent NAs in integer arrays. For example:

```
In [20]: s = pd.Series([1, 2, 3, 4, 5], index=list("abcde"))

In [21]: s
Out[21]:
a    1
b    2
c    3
d    4
e    5
dtype: int64

In [22]: s.dtype
Out[22]: dtype('int64')

In [23]: s2 = s.reindex(["a", "b", "c", "f", "u"])

In [24]: s2
Out[24]:
a    1.0
b    2.0
c    3.0
f    NaN
u    NaN
dtype: float64

In [25]: s2.dtype
Out[25]: dtype('float64')
```

This trade-off is made largely for memory and performance reasons, and also so that the resulting Series continues to be "numeric".

If you need to represent integers with possibly missing values, use one of the nullable-integer extension dtypes provided by pandas

- *Int8Dtype*
- *Int16Dtype*
- *Int32Dtype*
- *Int64Dtype*

```
In [26]: s_int = pd.Series([1, 2, 3, 4, 5], index=list("abcde"), dtype=pd.
↪Int64Dtype())

In [27]: s_int
Out[27]:
a    1
b    2
c    3
d    4
e    5
dtype: Int64

In [28]: s_int.dtype
Out[28]: Int64Dtype()

In [29]: s2_int = s_int.reindex(["a", "b", "c", "f", "u"])

In [30]: s2_int
Out[30]:
a       1
b       2
c       3
f    <NA>
u    <NA>
dtype: Int64

In [31]: s2_int.dtype
Out[31]: Int64Dtype()
```

See *Nullable integer data type* for more.

NA type promotions

When introducing NAs into an existing `Series` or `DataFrame` via *reindex()* or some other means, boolean and integer types will be promoted to a different dtype in order to store the NAs. The promotions are summarized in this table:

Typeclass	Promotion dtype for storing NAs
`floating`	no change
`object`	no change
`integer`	cast to `float64`
`boolean`	cast to `object`

While this may seem like a heavy trade-off, I have found very few cases where this is an issue in practice i.e. storing values greater than 2**53. Some explanation for the motivation is in the next section.

Why not make NumPy like R?

Many people have suggested that NumPy should simply emulate the NA support present in the more domain-specific statistical programming language R. Part of the reason is the NumPy type hierarchy:

Typeclass	Dtypes
numpy.floating	float16, float32, float64, float128
numpy.integer	int8, int16, int32, int64
numpy.unsignedinteger	uint8, uint16, uint32, uint64
numpy.object_	object_
numpy.bool_	bool_
numpy.character	string_, unicode_

The R language, by contrast, only has a handful of built-in data types: integer, numeric (floating-point), character, and boolean. NA types are implemented by reserving special bit patterns for each type to be used as the missing value. While doing this with the full NumPy type hierarchy would be possible, it would be a more substantial trade-off (especially for the 8- and 16-bit data types) and implementation undertaking.

An alternate approach is that of using masked arrays. A masked array is an array of data with an associated boolean *mask* denoting whether each value should be considered NA or not. I am personally not in love with this approach as I feel that overall it places a fairly heavy burden on the user and the library implementer. Additionally, it exacts a fairly high performance cost when working with numerical data compared with the simple approach of using NaN. Thus, I have chosen the Pythonic "practicality beats purity" approach and traded integer NA capability for a much simpler approach of using a special value in float and object arrays to denote NA, and promoting integer arrays to floating when NAs must be introduced.

2.26.4 Differences with NumPy

For Series and DataFrame objects, *var()* normalizes by N-1 to produce unbiased estimates of the sample variance, while NumPy's var normalizes by N, which measures the variance of the sample. Note that *cov()* normalizes by N-1 in both pandas and NumPy.

2.26.5 Thread-safety

As of pandas 0.11, pandas is not 100% thread safe. The known issues relate to the *copy()* method. If you are doing a lot of copying of DataFrame objects shared among threads, we recommend holding locks inside the threads where the data copying occurs.

See this link for more information.

2.26.6 Byte-ordering issues

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. A common symptom of this issue is an error like:

```
Traceback
    ...
ValueError: Big-endian buffer not supported on little-endian compiler
```

To deal with this issue you should convert the underlying NumPy array to the native system byte order *before* passing it to Series or DataFrame constructors using something similar to the following:

```
In [32]: x = np.array(list(range(10)), ">i4")  # big endian

In [33]: newx = x.byteswap().newbyteorder()  # force native byteorder

In [34]: s = pd.Series(newx)
```

See the NumPy documentation on byte order for more details.

2.27 Cookbook

This is a repository for *short and sweet* examples and links for useful pandas recipes. We encourage users to add to this documentation.

Adding interesting links and/or inline examples to this section is a great *First Pull Request*.

Simplified, condensed, new-user friendly, in-line examples have been inserted where possible to augment the Stack-Overflow and GitHub links. Many of the links contain expanded information, above what the in-line examples offer.

pandas (pd) and Numpy (np) are the only two abbreviated imported modules. The rest are kept explicitly imported for newer users.

2.27.1 Idioms

These are some neat pandas `idioms`

if-then/if-then-else on one column, and assignment to another one or more columns:

```
In [1]: df = pd.DataFrame(
   ...:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -50]}
   ...: )
   ...:

In [2]: df
Out[2]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50
```

if-then...

An if-then on one column

```
In [3]: df.loc[df.AAA >= 5, "BBB"] = -1

In [4]: df
Out[4]:
   AAA  BBB  CCC
0    4   10  100
1    5   -1   50
2    6   -1  -30
3    7   -1  -50
```

An if-then with assignment to 2 columns:

```
In [5]: df.loc[df.AAA >= 5, ["BBB", "CCC"]] = 555

In [6]: df
Out[6]:
   AAA  BBB  CCC
0    4   10  100
1    5  555  555
2    6  555  555
3    7  555  555
```

Add another line with different logic, to do the -else

```
In [7]: df.loc[df.AAA < 5, ["BBB", "CCC"]] = 2000

In [8]: df
Out[8]:
   AAA   BBB   CCC
0    4  2000  2000
1    5   555   555
2    6   555   555
3    7   555   555
```

Or use pandas where after you've set up a mask

```
In [9]: df_mask = pd.DataFrame(
   ...:     {"AAA": [True] * 4, "BBB": [False] * 4, "CCC": [True, False] * 2}
   ...: )
   ...:

In [10]: df.where(df_mask, -1000)
Out[10]:
   AAA   BBB   CCC
0    4 -1000  2000
1    5 -1000 -1000
2    6 -1000   555
3    7 -1000 -1000
```

if-then-else using NumPy's where()

```
In [11]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}
   ....: )
   ....:

In [12]: df
Out[12]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [13]: df["logic"] = np.where(df["AAA"] > 5, "high", "low")

In [14]: df
```

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```
Out[14]:
   AAA  BBB  CCC logic
0    4   10  100   low
1    5   20   50   low
2    6   30  -30  high
3    7   40  -50  high
```

Splitting

Split a frame with a boolean criterion

```
In [15]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}
   ....: )
   ....:

In [16]: df
Out[16]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [17]: df[df.AAA <= 5]
Out[17]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50

In [18]: df[df.AAA > 5]
Out[18]:
   AAA  BBB  CCC
2    6   30  -30
3    7   40  -50
```

Building criteria

Select with multi-column criteria

```
In [19]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}
   ....: )
   ....:

In [20]: df
Out[20]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50
```

. . . and (without assignment returns a Series)

```
In [21]: df.loc[(df["BBB"] < 25) & (df["CCC"] >= -40), "AAA"]
Out[21]:
0    4
1    5
Name: AAA, dtype: int64
```

. . . or (without assignment returns a Series)

```
In [22]: df.loc[(df["BBB"] > 25) | (df["CCC"] >= -40), "AAA"]
Out[22]:
0    4
1    5
2    6
3    7
Name: AAA, dtype: int64
```

. . . or (with assignment modifies the DataFrame.)

```
In [23]: df.loc[(df["BBB"] > 25) | (df["CCC"] >= 75), "AAA"] = 0.1

In [24]: df
Out[24]:
   AAA  BBB  CCC
0  0.1   10  100
1  5.0   20   50
2  0.1   30  -30
3  0.1   40  -50
```

Select rows with data closest to certain value using argsort

```
In [25]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}
   ....: )
   ....:

In [26]: df
Out[26]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [27]: aValue = 43.0

In [28]: df.loc[(df.CCC - aValue).abs().argsort()]
Out[28]:
   AAA  BBB  CCC
1    5   20   50
0    4   10  100
2    6   30  -30
3    7   40  -50
```

Dynamically reduce a list of criteria using a binary operators

```
In [29]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}
   ....: )
   ....:

In [30]: df
Out[30]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [31]: Crit1 = df.AAA <= 5.5

In [32]: Crit2 = df.BBB == 10.0

In [33]: Crit3 = df.CCC > -40.0
```

One could hard code:

```
In [34]: AllCrit = Crit1 & Crit2 & Crit3
```

...Or it can be done with a list of dynamically built criteria

```
In [35]: import functools

In [36]: CritList = [Crit1, Crit2, Crit3]

In [37]: AllCrit = functools.reduce(lambda x, y: x & y, CritList)

In [38]: df[AllCrit]
Out[38]:
   AAA  BBB  CCC
0    4   10  100
```

2.27.2 Selection

Dataframes

The *indexing* docs.

Using both row labels and value conditionals

```
In [39]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}
   ....: )
   ....:

In [40]: df
Out[40]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
```

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```
2    6   30  -30
3    7   40  -50

In [41]: df[(df.AAA <= 6) & (df.index.isin([0, 2, 4]))]
Out[41]:
   AAA  BBB  CCC
0    4   10  100
2    6   30  -30
```

Use loc for label-oriented slicing and iloc positional slicing

```
In [42]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]},
   ....:     index=["foo", "bar", "boo", "kar"],
   ....: )
   ....:
```

There are 2 explicit slicing methods, with a third general case

1. Positional-oriented (Python slicing style : exclusive of end)
2. Label-oriented (Non-Python slicing style : inclusive of end)
3. General (Either slicing style : depends on if the slice contains labels or positions)

```
In [43]: df.loc["bar":"kar"]  # Label
Out[43]:
     AAA  BBB  CCC
bar    5   20   50
boo    6   30  -30
kar    7   40  -50

# Generic
In [44]: df[0:3]
Out[44]:
     AAA  BBB  CCC
foo    4   10  100
bar    5   20   50
boo    6   30  -30

In [45]: df["bar":"kar"]
Out[45]:
     AAA  BBB  CCC
bar    5   20   50
boo    6   30  -30
kar    7   40  -50
```

Ambiguity arises when an index consists of integers with a non-zero start or non-unit increment.

```
In [46]: data = {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}

In [47]: df2 = pd.DataFrame(data=data, index=[1, 2, 3, 4])  # Note index starts at 1.

In [48]: df2.iloc[1:3]  # Position-oriented
Out[48]:
   AAA  BBB  CCC
```

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```
2    5   20   50
3    6   30  -30

In [49]: df2.loc[1:3]  # Label-oriented
Out[49]:
   AAA  BBB  CCC
1    4   10  100
2    5   20   50
3    6   30  -30
```

Using inverse operator (~) to take the complement of a mask

```
In [50]: df = pd.DataFrame(
   ....:     {"AAA": [4, 5, 6, 7], "BBB": [10, 20, 30, 40], "CCC": [100, 50, -30, -
↪50]}
   ....: )
   ....:

In [51]: df
Out[51]:
   AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [52]: df[~((df.AAA <= 6) & (df.index.isin([0, 2, 4])))]
Out[52]:
   AAA  BBB  CCC
1    5   20   50
3    7   40  -50
```

New columns

Efficiently and dynamically creating new columns using applymap

```
In [53]: df = pd.DataFrame({"AAA": [1, 2, 1, 3], "BBB": [1, 1, 2, 2], "CCC": [2, 1, 3,
↪ 1]})

In [54]: df
Out[54]:
   AAA  BBB  CCC
0    1    1    2
1    2    1    1
2    1    2    3
3    3    2    1

In [55]: source_cols = df.columns  # Or some subset would work too

In [56]: new_cols = [str(x) + "_cat" for x in source_cols]

In [57]: categories = {1: "Alpha", 2: "Beta", 3: "Charlie"}

In [58]: df[new_cols] = df[source_cols].applymap(categories.get)
```

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```
In [59]: df
Out[59]:
   AAA  BBB  CCC  AAA_cat BBB_cat  CCC_cat
0    1    1    2    Alpha   Alpha     Beta
1    2    1    1     Beta   Alpha    Alpha
2    1    2    3    Alpha    Beta  Charlie
3    3    2    1  Charlie    Beta    Alpha
```

Keep other columns when using min() with groupby

```
In [60]: df = pd.DataFrame(
   ....:     {"AAA": [1, 1, 1, 2, 2, 2, 3, 3], "BBB": [2, 1, 3, 4, 5, 1, 2, 3]}
   ....: )
   ....:

In [61]: df
Out[61]:
   AAA  BBB
0    1    2
1    1    1
2    1    3
3    2    4
4    2    5
5    2    1
6    3    2
7    3    3
```

Method 1 : idxmin() to get the index of the minimums

```
In [62]: df.loc[df.groupby("AAA")["BBB"].idxmin()]
Out[62]:
   AAA  BBB
1    1    1
5    2    1
6    3    2
```

Method 2 : sort then take first of each

```
In [63]: df.sort_values(by="BBB").groupby("AAA", as_index=False).first()
Out[63]:
   AAA  BBB
0    1    1
1    2    1
2    3    2
```

Notice the same results, with the exception of the index.

2.27.3 Multiindexing

The *multindexing* docs.

Creating a MultiIndex from a labeled frame

```
In [64]: df = pd.DataFrame(
   ....:     {
   ....:         "row": [0, 1, 2],
   ....:         "One_X": [1.1, 1.1, 1.1],
   ....:         "One_Y": [1.2, 1.2, 1.2],
   ....:         "Two_X": [1.11, 1.11, 1.11],
   ....:         "Two_Y": [1.22, 1.22, 1.22],
   ....:     }
   ....: )
   ....:

In [65]: df
Out[65]:
   row  One_X  One_Y  Two_X  Two_Y
0    0    1.1    1.2   1.11   1.22
1    1    1.1    1.2   1.11   1.22
2    2    1.1    1.2   1.11   1.22

# As Labelled Index
In [66]: df = df.set_index("row")

In [67]: df
Out[67]:
     One_X  One_Y  Two_X  Two_Y
row
0      1.1    1.2   1.11   1.22
1      1.1    1.2   1.11   1.22
2      1.1    1.2   1.11   1.22

# With Hierarchical Columns
In [68]: df.columns = pd.MultiIndex.from_tuples([tuple(c.split("_")) for c in df.
↪columns])

In [69]: df
Out[69]:
     One         Two
       X    Y      X     Y
row
0    1.1  1.2   1.11  1.22
1    1.1  1.2   1.11  1.22
2    1.1  1.2   1.11  1.22

# Now stack & Reset
In [70]: df = df.stack(0).reset_index(1)

In [71]: df
Out[71]:
    level_1     X     Y
row
0       One  1.10  1.20
0       Two  1.11  1.22
1       One  1.10  1.20
```

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```
1       Two  1.11  1.22
2       One  1.10  1.20
2       Two  1.11  1.22

# And fix the labels (Notice the label 'level_1' got added automatically)
In [72]: df.columns = ["Sample", "All_X", "All_Y"]

In [73]: df
Out[73]:
    Sample  All_X  All_Y
row
0      One   1.10   1.20
0      Two   1.11   1.22
1      One   1.10   1.20
1      Two   1.11   1.22
2      One   1.10   1.20
2      Two   1.11   1.22
```

Arithmetic

Performing arithmetic with a MultiIndex that needs broadcasting

```
In [74]: cols = pd.MultiIndex.from_tuples(
   ....:     [(x, y) for x in ["A", "B", "C"] for y in ["O", "I"]]
   ....: )
   ....:

In [75]: df = pd.DataFrame(np.random.randn(2, 6), index=["n", "m"], columns=cols)

In [76]: df
Out[76]:
          A                   B                   C
          O         I         O         I         O         I
n  0.469112 -0.282863 -1.509059 -1.135632  1.212112 -0.173215
m  0.119209 -1.044236 -0.861849 -2.104569 -0.494929  1.071804

In [77]: df = df.div(df["C"], level=1)

In [78]: df
Out[78]:
          A                   B             C
          O         I         O         I   O    I
n  0.387021  1.633022 -1.244983  6.556214  1.0  1.0
m -0.240860 -0.974279  1.741358 -1.963577  1.0  1.0
```

Slicing

Slicing a MultiIndex with xs

```
In [79]: coords = [("AA", "one"), ("AA", "six"), ("BB", "one"), ("BB", "two"), ("BB",
↪"six")]

In [80]: index = pd.MultiIndex.from_tuples(coords)

In [81]: df = pd.DataFrame([11, 22, 33, 44, 55], index, ["MyData"])

In [82]: df
Out[82]:
        MyData
AA one      11
   six      22
BB one      33
   two      44
   six      55
```

To take the cross section of the 1st level and 1st axis the index:

```
# Note : level and axis are optional, and default to zero
In [83]: df.xs("BB", level=0, axis=0)
Out[83]:
     MyData
one      33
two      44
six      55
```

. . . and now the 2nd level of the 1st axis.

```
In [84]: df.xs("six", level=1, axis=0)
Out[84]:
    MyData
AA      22
BB      55
```

Slicing a MultiIndex with xs, method #2

```
In [85]: import itertools

In [86]: index = list(itertools.product(["Ada", "Quinn", "Violet"], ["Comp", "Math",
↪"Sci"]))

In [87]: headr = list(itertools.product(["Exams", "Labs"], ["I", "II"]))

In [88]: indx = pd.MultiIndex.from_tuples(index, names=["Student", "Course"])

In [89]: cols = pd.MultiIndex.from_tuples(headr)  # Notice these are un-named

In [90]: data = [[70 + x + y + (x * y) % 3 for x in range(4)] for y in range(9)]

In [91]: df = pd.DataFrame(data, indx, cols)

In [92]: df
Out[92]:
               Exams     Labs
```

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```
                    I  II    I  II
Student Course
Ada     Comp       70  71   72  73
        Math       71  73   75  74
        Sci        72  75   75  75
Quinn   Comp       73  74   75  76
        Math       74  76   78  77
        Sci        75  78   78  78
Violet  Comp       76  77   78  79
        Math       77  79   81  80
        Sci        78  81   81  81

In [93]: All = slice(None)

In [94]: df.loc["Violet"]
Out[94]:
       Exams     Labs
           I  II    I  II
Course
Comp      76  77   78  79
Math      77  79   81  80
Sci       78  81   81  81

In [95]: df.loc[(All, "Math"), All]
Out[95]:
                Exams     Labs
                    I  II    I  II
Student Course
Ada     Math       71  73   75  74
Quinn   Math       74  76   78  77
Violet  Math       77  79   81  80

In [96]: df.loc[(slice("Ada", "Quinn"), "Math"), All]
Out[96]:
                Exams     Labs
                    I  II    I  II
Student Course
Ada     Math       71  73   75  74
Quinn   Math       74  76   78  77

In [97]: df.loc[(All, "Math"), ("Exams")]
Out[97]:
                   I  II
Student Course
Ada     Math      71  73
Quinn   Math      74  76
Violet  Math      77  79

In [98]: df.loc[(All, "Math"), (All, "II")]
Out[98]:
                Exams Labs
                   II   II
Student Course
Ada     Math       73   74
Quinn   Math       76   77
Violet  Math       79   80
```

Setting portions of a MultiIndex with xs

Sorting

Sort by specific column or an ordered list of columns, with a MultiIndex

```
In [99]: df.sort_values(by=("Labs", "II"), ascending=False)
Out[99]:
                Exams     Labs
                    I  II     I  II
Student Course
Violet  Sci        78  81    81  81
        Math       77  79    81  80
        Comp       76  77    78  79
Quinn   Sci        75  78    78  78
        Math       74  76    78  77
        Comp       73  74    75  76
Ada     Sci        72  75    75  75
        Math       71  73    75  74
        Comp       70  71    72  73
```

Partial selection, the need for sortedness;

Levels

Prepending a level to a multiindex

Flatten Hierarchical columns

2.27.4 Missing data

The *missing data* docs.

Fill forward a reversed timeseries

```
In [100]: df = pd.DataFrame(
   .....:     np.random.randn(6, 1),
   .....:     index=pd.date_range("2013-08-01", periods=6, freq="B"),
   .....:     columns=list("A"),
   .....: )
   .....:

In [101]: df.loc[df.index[3], "A"] = np.nan

In [102]: df
Out[102]:
                   A
2013-08-01  0.721555
2013-08-02 -0.706771
2013-08-05 -1.039575
2013-08-06       NaN
2013-08-07 -0.424972
2013-08-08  0.567020

In [103]: df.reindex(df.index[::-1]).ffill()
```

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```
Out[103]:
                   A
2013-08-08  0.567020
2013-08-07 -0.424972
2013-08-06 -0.424972
2013-08-05 -1.039575
2013-08-02 -0.706771
2013-08-01  0.721555
```

cumsum reset at NaN values

Replace

Using replace with backrefs

2.27.5 Grouping

The *grouping* docs.

Basic grouping with apply

Unlike agg, apply's callable is passed a sub-DataFrame which gives you access to all the columns

```
In [104]: df = pd.DataFrame(
   .....:     {
   .....:         "animal": "cat dog cat fish dog cat cat".split(),
   .....:         "size": list("SSMMMLL"),
   .....:         "weight": [8, 10, 11, 1, 20, 12, 12],
   .....:         "adult": [False] * 5 + [True] * 2,
   .....:     }
   .....: )
   .....:

In [105]: df
Out[105]:
  animal size  weight  adult
0    cat    S       8  False
1    dog    S      10  False
2    cat    M      11  False
3   fish    M       1  False
4    dog    M      20  False
5    cat    L      12   True
6    cat    L      12   True

# List the size of the animals with the highest weight.
In [106]: df.groupby("animal").apply(lambda subf: subf["size"][subf["weight"].
 ↪idxmax()])
Out[106]:
animal
cat     L
dog     M
fish    M
dtype: object
```

Using get_group

```
In [107]: gb = df.groupby(["animal"])

In [108]: gb.get_group("cat")
Out[108]:
  animal size  weight  adult
0    cat    S       8  False
2    cat    M      11  False
5    cat    L      12   True
6    cat    L      12   True
```

Apply to different items in a group

```
In [109]: def GrowUp(x):
   .....:     avg_weight = sum(x[x["size"] == "S"].weight * 1.5)
   .....:     avg_weight += sum(x[x["size"] == "M"].weight * 1.25)
   .....:     avg_weight += sum(x[x["size"] == "L"].weight)
   .....:     avg_weight /= len(x)
   .....:     return pd.Series(["L", avg_weight, True], index=["size", "weight",
↪"adult"])
   .....:

In [110]: expected_df = gb.apply(GrowUp)

In [111]: expected_df
Out[111]:
       size   weight  adult
animal
cat       L  12.4375   True
dog       L  20.0000   True
fish      L   1.2500   True
```

Expanding apply

```
In [112]: S = pd.Series([i / 100.0 for i in range(1, 11)])

In [113]: def cum_ret(x, y):
   .....:     return x * (1 + y)
   .....:

In [114]: def red(x):
   .....:     return functools.reduce(cum_ret, x, 1.0)
   .....:

In [115]: S.expanding().apply(red, raw=True)
Out[115]:
0    1.010000
1    1.030200
2    1.061106
3    1.103550
4    1.158728
5    1.228251
6    1.314229
7    1.419367
8    1.547110
9    1.701821
dtype: float64
```

Replacing some values with mean of the rest of a group

```
In [116]: df = pd.DataFrame({"A": [1, 1, 2, 2], "B": [1, -1, 1, 2]})

In [117]: gb = df.groupby("A")

In [118]: def replace(g):
   .....:     mask = g < 0
   .....:     return g.where(mask, g[~mask].mean())
   .....:

In [119]: gb.transform(replace)
Out[119]:
     B
0  1.0
1 -1.0
2  1.5
3  1.5
```

Sort groups by aggregated data

```
In [120]: df = pd.DataFrame(
   .....:     {
   .....:         "code": ["foo", "bar", "baz"] * 2,
   .....:         "data": [0.16, -0.21, 0.33, 0.45, -0.59, 0.62],
   .....:         "flag": [False, True] * 3,
   .....:     }
   .....: )
   .....:

In [121]: code_groups = df.groupby("code")

In [122]: agg_n_sort_order = code_groups[["data"]].transform(sum).sort_values(by="data
↪")

In [123]: sorted_df = df.loc[agg_n_sort_order.index]

In [124]: sorted_df
Out[124]:
  code  data   flag
1  bar -0.21   True
4  bar -0.59  False
0  foo  0.16  False
3  foo  0.45   True
2  baz  0.33  False
5  baz  0.62   True
```

Create multiple aggregated columns

```
In [125]: rng = pd.date_range(start="2014-10-07", periods=10, freq="2min")

In [126]: ts = pd.Series(data=list(range(10)), index=rng)

In [127]: def MyCust(x):
   .....:     if len(x) > 2:
   .....:         return x[1] * 1.234
   .....:     return pd.NaT
   .....:
```

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```
In [128]: mhc = {"Mean": np.mean, "Max": np.max, "Custom": MyCust}

In [129]: ts.resample("5min").apply(mhc)
Out[129]:
Mean    2014-10-07 00:00:00      1.0
        2014-10-07 00:05:00      3.5
        2014-10-07 00:10:00      6.0
        2014-10-07 00:15:00      8.5
Max     2014-10-07 00:00:00        2
        2014-10-07 00:05:00        4
        2014-10-07 00:10:00        7
        2014-10-07 00:15:00        9
Custom  2014-10-07 00:00:00    1.234
        2014-10-07 00:05:00      NaT
        2014-10-07 00:10:00    7.404
        2014-10-07 00:15:00      NaT
dtype: object

In [130]: ts
Out[130]:
2014-10-07 00:00:00    0
2014-10-07 00:02:00    1
2014-10-07 00:04:00    2
2014-10-07 00:06:00    3
2014-10-07 00:08:00    4
2014-10-07 00:10:00    5
2014-10-07 00:12:00    6
2014-10-07 00:14:00    7
2014-10-07 00:16:00    8
2014-10-07 00:18:00    9
Freq: 2T, dtype: int64
```

Create a value counts column and reassign back to the DataFrame

```
In [131]: df = pd.DataFrame(
   .....:     {"Color": "Red Red Red Blue".split(), "Value": [100, 150, 50, 50]}
   .....: )
   .....:

In [132]: df
Out[132]:
  Color  Value
0   Red    100
1   Red    150
2   Red     50
3  Blue     50

In [133]: df["Counts"] = df.groupby(["Color"]).transform(len)

In [134]: df
Out[134]:
  Color  Value  Counts
0   Red    100       3
1   Red    150       3
2   Red     50       3
3  Blue     50       1
```

Shift groups of the values in a column based on the index

```
In [135]: df = pd.DataFrame(
   .....:     {"line_race": [10, 10, 8, 10, 10, 8], "beyer": [99, 102, 103, 103, 88,␣
↪100]},
   .....:     index=[
   .....:         "Last Gunfighter",
   .....:         "Last Gunfighter",
   .....:         "Last Gunfighter",
   .....:         "Paynter",
   .....:         "Paynter",
   .....:         "Paynter",
   .....:     ],
   .....: )
   .....:

In [136]: df
Out[136]:
                 line_race  beyer
Last Gunfighter         10     99
Last Gunfighter         10    102
Last Gunfighter          8    103
Paynter                 10    103
Paynter                 10     88
Paynter                  8    100

In [137]: df["beyer_shifted"] = df.groupby(level=0)["beyer"].shift(1)

In [138]: df
Out[138]:
                 line_race  beyer  beyer_shifted
Last Gunfighter         10     99            NaN
Last Gunfighter         10    102           99.0
Last Gunfighter          8    103          102.0
Paynter                 10    103            NaN
Paynter                 10     88          103.0
Paynter                  8    100           88.0
```

Select row with maximum value from each group

```
In [139]: df = pd.DataFrame(
   .....:     {
   .....:         "host": ["other", "other", "that", "this", "this"],
   .....:         "service": ["mail", "web", "mail", "mail", "web"],
   .....:         "no": [1, 2, 1, 2, 1],
   .....:     }
   .....: ).set_index(["host", "service"])
   .....:

In [140]: mask = df.groupby(level=0).agg("idxmax")

In [141]: df_count = df.loc[mask["no"]].reset_index()

In [142]: df_count
Out[142]:
    host service  no
0  other     web   2
1   that    mail   1
```

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```
2   this    mail   2
```

Grouping like Python's itertools.groupby

```
In [143]: df = pd.DataFrame([0, 1, 0, 1, 1, 1, 0, 1, 1], columns=["A"])

In [144]: df["A"].groupby((df["A"] != df["A"].shift()).cumsum()).groups
Out[144]: {1: [0], 2: [1], 3: [2], 4: [3, 4, 5], 5: [6], 6: [7, 8]}

In [145]: df["A"].groupby((df["A"] != df["A"].shift()).cumsum()).cumsum()
Out[145]:
0    0
1    1
2    0
3    1
4    2
5    3
6    0
7    1
8    2
Name: A, dtype: int64
```

Expanding data

Alignment and to-date

Rolling Computation window based on values instead of counts

Rolling Mean by Time Interval

Splitting

Splitting a frame

Create a list of dataframes, split using a delineation based on logic included in rows.

```
In [146]: df = pd.DataFrame(
   .....:     data={
   .....:         "Case": ["A", "A", "A", "B", "A", "A", "B", "A", "A"],
   .....:         "Data": np.random.randn(9),
   .....:     }
   .....: )
   .....:

In [147]: dfs = list(
   .....:     zip(
   .....:         *df.groupby(
   .....:             (1 * (df["Case"] == "B"))
   .....:             .cumsum()
   .....:             .rolling(window=3, min_periods=1)
   .....:             .median()
   .....:         )
   .....:     )
   .....: )[-1]
   .....:
```

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```
In [148]: dfs[0]
Out[148]:
  Case      Data
0    A  0.276232
1    A -1.087401
2    A -0.673690
3    B  0.113648

In [149]: dfs[1]
Out[149]:
  Case      Data
4    A -1.478427
5    A  0.524988
6    B  0.404705

In [150]: dfs[2]
Out[150]:
  Case      Data
7    A  0.577046
8    A -1.715002
```

Pivot

The *Pivot* docs.

Partial sums and subtotals

```
In [151]: df = pd.DataFrame(
   .....:     data={
   .....:         "Province": ["ON", "QC", "BC", "AL", "AL", "MN", "ON"],
   .....:         "City": [
   .....:             "Toronto",
   .....:             "Montreal",
   .....:             "Vancouver",
   .....:             "Calgary",
   .....:             "Edmonton",
   .....:             "Winnipeg",
   .....:             "Windsor",
   .....:         ],
   .....:         "Sales": [13, 6, 16, 8, 4, 3, 1],
   .....:     }
   ..... )
   .....:

In [152]: table = pd.pivot_table(
   .....:     df,
   .....:     values=["Sales"],
   .....:     index=["Province"],
   .....:     columns=["City"],
   .....:     aggfunc=np.sum,
   .....:     margins=True,
   ..... )
   .....:
```

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```
In [153]: table.stack("City")
Out[153]:
                     Sales
Province City
AL       All          12.0
         Calgary       8.0
         Edmonton      4.0
BC       All          16.0
         Vancouver    16.0
...                    ...
All      Montreal      6.0
         Toronto      13.0
         Vancouver    16.0
         Windsor       1.0
         Winnipeg      3.0

[20 rows x 1 columns]
```

Frequency table like plyr in R

```
In [154]: grades = [48, 99, 75, 80, 42, 80, 72, 68, 36, 78]

In [155]: df = pd.DataFrame(
   .....:     {
   .....:         "ID": ["x%d" % r for r in range(10)],
   .....:         "Gender": ["F", "M", "F", "M", "F", "M", "F", "M", "M", "M"],
   .....:         "ExamYear": [
   .....:             "2007",
   .....:             "2007",
   .....:             "2007",
   .....:             "2008",
   .....:             "2008",
   .....:             "2008",
   .....:             "2008",
   .....:             "2009",
   .....:             "2009",
   .....:             "2009",
   .....:         ],
   .....:         "Class": [
   .....:             "algebra",
   .....:             "stats",
   .....:             "bio",
   .....:             "algebra",
   .....:             "algebra",
   .....:             "stats",
   .....:             "stats",
   .....:             "algebra",
   .....:             "bio",
   .....:             "bio",
   .....:         ],
   .....:         "Participated": [
   .....:             "yes",
   .....:             "yes",
   .....:             "yes",
   .....:             "yes",
   .....:             "no",
   .....:             "yes",
```

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```
   .....:             "yes",
   .....:             "yes",
   .....:             "yes",
   .....:             "yes",
   .....:         ],
   .....:         "Passed": ["yes" if x > 50 else "no" for x in grades],
   .....:         "Employed": [
   .....:             True,
   .....:             True,
   .....:             True,
   .....:             False,
   .....:             False,
   .....:             False,
   .....:             False,
   .....:             True,
   .....:             True,
   .....:             False,
   .....:         ],
   .....:         "Grade": grades,
   .....:     }
   ..... )
   .....:

In [156]: df.groupby("ExamYear").agg(
   .....:     {
   .....:         "Participated": lambda x: x.value_counts()["yes"],
   .....:         "Passed": lambda x: sum(x == "yes"),
   .....:         "Employed": lambda x: sum(x),
   .....:         "Grade": lambda x: sum(x) / len(x),
   .....:     }
   ..... )
   .....:
Out[156]:
          Participated  Passed  Employed      Grade
ExamYear
2007                 3       2         3  74.000000
2008                 3       3         0  68.500000
2009                 3       2         2  60.666667
```

Plot pandas DataFrame with year over year data

To create year and month cross tabulation:

```
In [157]: df = pd.DataFrame(
   .....:     {"value": np.random.randn(36)},
   .....:     index=pd.date_range("2011-01-01", freq="M", periods=36),
   ..... )
   .....:

In [158]: pd.pivot_table(
   .....:     df, index=df.index.month, columns=df.index.year, values="value",␣
↪aggfunc="sum"
   ..... )
   .....:
Out[158]:
        2011      2012      2013
1  -1.039268 -0.968914  2.565646
```

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```
2  -0.370647 -1.294524  1.431256
3  -1.157892  0.413738  1.340309
4  -1.344312  0.276662 -1.170299
5   0.844885 -0.472035 -0.226169
6   1.075770 -0.013960  0.410835
7  -0.109050 -0.362543  0.813850
8   1.643563 -0.006154  0.132003
9  -1.469388 -0.923061 -0.827317
10  0.357021  0.895717 -0.076467
11 -0.674600  0.805244 -1.187678
12 -1.776904 -1.206412  1.130127
```

Apply

Rolling apply to organize - Turning embedded lists into a MultiIndex frame

```
In [159]: df = pd.DataFrame(
   .....:     data={
   .....:         "A": [[2, 4, 8, 16], [100, 200], [10, 20, 30]],
   .....:         "B": [["a", "b", "c"], ["jj", "kk"], ["ccc"]],
   .....:     },
   .....:     index=["I", "II", "III"],
   .....: )
   .....:

In [160]: def SeriesFromSubList(aList):
   .....:     return pd.Series(aList)
   .....:

In [161]: df_orgz = pd.concat(
   .....:     {ind: row.apply(SeriesFromSubList) for ind, row in df.iterrows()}
   .....: )
   .....:

In [162]: df_orgz
Out[162]:
         0     1     2     3
I   A    2     4     8  16.0
    B    a     b     c   NaN
II  A  100   200   NaN   NaN
    B   jj    kk   NaN   NaN
III A   10  20.0  30.0   NaN
    B  ccc   NaN   NaN   NaN
```

Rolling apply with a DataFrame returning a Series

Rolling Apply to multiple columns where function calculates a Series before a Scalar from the Series is returned

```
In [163]: df = pd.DataFrame(
   .....:     data=np.random.randn(2000, 2) / 10000,
   .....:     index=pd.date_range("2001-01-01", periods=2000),
   .....:     columns=["A", "B"],
   .....: )
   .....:
```

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```
In [164]: df
Out[164]:
                   A         B
2001-01-01 -0.000144 -0.000141
2001-01-02  0.000161  0.000102
2001-01-03  0.000057  0.000088
2001-01-04 -0.000221  0.000097
2001-01-05 -0.000201 -0.000041
...              ...       ...
2006-06-19  0.000040 -0.000235
2006-06-20 -0.000123 -0.000021
2006-06-21 -0.000113  0.000114
2006-06-22  0.000136  0.000109
2006-06-23  0.000027  0.000030

[2000 rows x 2 columns]

In [165]: def gm(df, const):
   .....:     v = ((((df["A"] + df["B"]) + 1).cumprod()) - 1) * const
   .....:     return v.iloc[-1]
   .....:

In [166]: s = pd.Series(
   .....:     {
   .....:         df.index[i]: gm(df.iloc[i: min(i + 51, len(df) - 1)], 5)
   .....:         for i in range(len(df) - 50)
   .....:     }
   .....: )
   .....:

In [167]: s
Out[167]:
2001-01-01    0.000930
2001-01-02    0.002615
2001-01-03    0.001281
2001-01-04    0.001117
2001-01-05    0.002772
                ...
2006-04-30    0.003296
2006-05-01    0.002629
2006-05-02    0.002081
2006-05-03    0.004247
2006-05-04    0.003928
Length: 1950, dtype: float64
```

Rolling apply with a DataFrame returning a Scalar

Rolling Apply to multiple columns where function returns a Scalar (Volume Weighted Average Price)

```
In [168]: rng = pd.date_range(start="2014-01-01", periods=100)

In [169]: df = pd.DataFrame(
   .....:     {
   .....:         "Open": np.random.randn(len(rng)),
   .....:         "Close": np.random.randn(len(rng)),
   .....:         "Volume": np.random.randint(100, 2000, len(rng)),
   .....:     },
```

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```
   .....:     index=rng,
   .....: )
   .....:

In [170]: df
Out[170]:
                 Open     Close  Volume
2014-01-01 -1.611353 -0.492885    1219
2014-01-02 -3.000951  0.445794    1054
2014-01-03 -0.138359 -0.076081    1381
2014-01-04  0.301568  1.198259    1253
2014-01-05  0.276381 -0.669831    1728
...              ...       ...     ...
2014-04-06 -0.040338  0.937843    1188
2014-04-07  0.359661 -0.285908    1864
2014-04-08  0.060978  1.714814     941
2014-04-09  1.759055 -0.455942    1065
2014-04-10  0.138185 -1.147008    1453

[100 rows x 3 columns]

In [171]: def vwap(bars):
   .....:     return (bars.Close * bars.Volume).sum() / bars.Volume.sum()
   .....:

In [172]: window = 5

In [173]: s = pd.concat(
   .....:     [
   .....:         (pd.Series(vwap(df.iloc[i: i + window]), index=[df.index[i +
↪window]]))
   .....:         for i in range(len(df) - window)
   .....:     ]
   .....: )
   .....:

In [174]: s.round(2)
Out[174]:
2014-01-06    0.02
2014-01-07    0.11
2014-01-08    0.10
2014-01-09    0.07
2014-01-10   -0.29
              ...
2014-04-06   -0.63
2014-04-07   -0.02
2014-04-08   -0.03
2014-04-09    0.34
2014-04-10    0.29
Length: 95, dtype: float64
```

2.27.6 Timeseries

Between times

Using indexer between time

Constructing a datetime range that excludes weekends and includes only certain times

Vectorized Lookup

Aggregation and plotting time series

Turn a matrix with hours in columns and days in rows into a continuous row sequence in the form of a time series. How to rearrange a Python pandas DataFrame?

Dealing with duplicates when reindexing a timeseries to a specified frequency

Calculate the first day of the month for each entry in a DatetimeIndex

```
In [175]: dates = pd.date_range("2000-01-01", periods=5)

In [176]: dates.to_period(freq="M").to_timestamp()
Out[176]:
DatetimeIndex(['2000-01-01', '2000-01-01', '2000-01-01', '2000-01-01',
               '2000-01-01'],
              dtype='datetime64[ns]', freq=None)
```

Resampling

The *Resample* docs.

Using Grouper instead of TimeGrouper for time grouping of values

Time grouping with some missing values

Valid frequency arguments to Grouper *Timeseries*

Grouping using a MultiIndex

Using TimeGrouper and another grouping to create subgroups, then apply a custom function

Resampling with custom periods

Resample intraday frame without adding new days

Resample minute data

Resample with groupby

2.27.7 Merge

The *Concat* docs. The *Join* docs.

Append two dataframes with overlapping index (emulate R rbind)

```
In [177]: rng = pd.date_range("2000-01-01", periods=6)

In [178]: df1 = pd.DataFrame(np.random.randn(6, 3), index=rng, columns=["A", "B", "C
↪"])

In [179]: df2 = df1.copy()
```

Depending on df construction, `ignore_index` may be needed

```
In [180]: df = df1.append(df2, ignore_index=True)

In [181]: df
Out[181]:
           A         B         C
0  -0.870117 -0.479265 -0.790855
1   0.144817  1.726395 -0.464535
2  -0.821906  1.597605  0.187307
3  -0.128342 -1.511638 -0.289858
4   0.399194 -1.430030 -0.639760
5   1.115116 -2.012600  1.810662
6  -0.870117 -0.479265 -0.790855
7   0.144817  1.726395 -0.464535
8  -0.821906  1.597605  0.187307
9  -0.128342 -1.511638 -0.289858
10  0.399194 -1.430030 -0.639760
11  1.115116 -2.012600  1.810662
```

Self Join of a DataFrame

```
In [182]: df = pd.DataFrame(
   .....:     data={
   .....:         "Area": ["A"] * 5 + ["C"] * 2,
   .....:         "Bins": [110] * 2 + [160] * 3 + [40] * 2,
   .....:         "Test_0": [0, 1, 0, 1, 2, 0, 1],
   .....:         "Data": np.random.randn(7),
   .....:     }
   .....: )
   .....:

In [183]: df
Out[183]:
  Area  Bins  Test_0      Data
0    A   110       0 -0.433937
1    A   110       1 -0.160552
2    A   160       0  0.744434
3    A   160       1  1.754213
4    A   160       2  0.000850
5    C    40       0  0.342243
6    C    40       1  1.070599

In [184]: df["Test_1"] = df["Test_0"] - 1

In [185]: pd.merge(
   .....:     df,
   .....:     df,
   .....:     left_on=["Bins", "Area", "Test_0"],
   .....:     right_on=["Bins", "Area", "Test_1"],
   .....:     suffixes=("_L", "_R"),
   .....: )
   .....:
Out[185]:
  Area  Bins  Test_0_L    Data_L  Test_1_L  Test_0_R    Data_R  Test_1_R
0    A   110         0 -0.433937        -1         1 -0.160552         0
1    A   160         0  0.744434        -1         1  1.754213         0
2    A   160         1  1.754213         0         2  0.000850         1
```

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```
3    C    40         0  0.342243        -1         1  1.070599         0
```

How to set the index and join

KDB like asof join

Join with a criteria based on the values

Using searchsorted to merge based on values inside a range

2.27.8 Plotting

The *Plotting* docs.

Make Matplotlib look like R

Setting x-axis major and minor labels

Plotting multiple charts in an IPython Jupyter notebook

Creating a multi-line plot

Plotting a heatmap

Annotate a time-series plot

Annotate a time-series plot #2

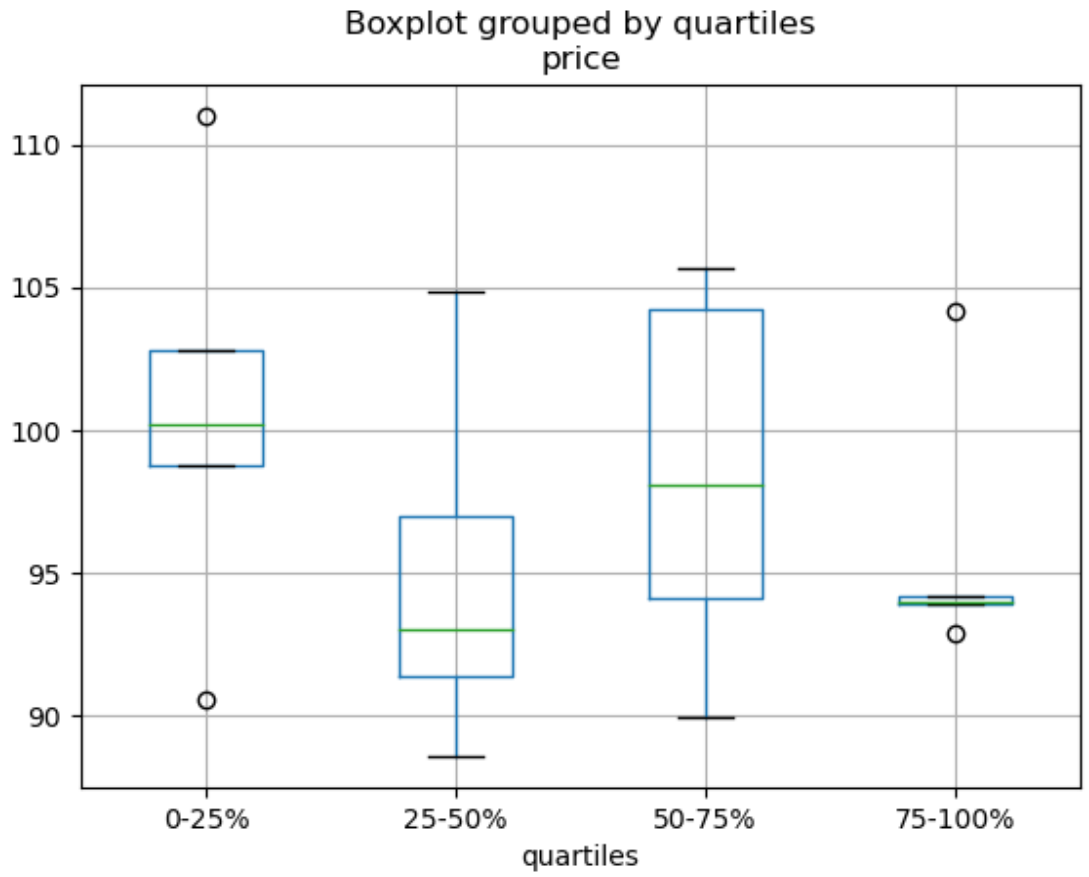
Generate Embedded plots in excel files using Pandas, Vincent and xlsxwriter

Boxplot for each quartile of a stratifying variable

```
In [186]: df = pd.DataFrame(
   .....:     {
   .....:         "stratifying_var": np.random.uniform(0, 100, 20),
   .....:         "price": np.random.normal(100, 5, 20),
   .....:     }
   .....: )
   .....:

In [187]: df["quartiles"] = pd.qcut(
   .....:     df["stratifying_var"], 4, labels=["0-25%", "25-50%", "50-75%", "75-100%
↪"]
   .....: )
   .....:

In [188]: df.boxplot(column="price", by="quartiles")
Out[188]: <AxesSubplot:title={'center':'price'}, xlabel='quartiles'>
```



2.27.9 Data in/out

Performance comparison of SQL vs HDF5

CSV

The *CSV* docs

read_csv in action

appending to a csv

Reading a csv chunk-by-chunk

Reading only certain rows of a csv chunk-by-chunk

Reading the first few lines of a frame

Reading a file that is compressed but not by `gzip/bz2` (the native compressed formats which `read_csv` understands). This example shows a `WinZipped` file, but is a general application of opening the file within a context manager and using that handle to read. See here

Inferring dtypes from a file

Dealing with bad lines

Dealing with bad lines II

Reading CSV with Unix timestamps and converting to local timezone

Write a multi-row index CSV without writing duplicates

Reading multiple files to create a single DataFrame

The best way to combine multiple files into a single DataFrame is to read the individual frames one by one, put all of the individual frames into a list, and then combine the frames in the list using `pd.concat()`:

```
In [189]: for i in range(3):
   .....:     data = pd.DataFrame(np.random.randn(10, 4))
   .....:     data.to_csv("file_{}.csv".format(i))
   .....:

In [190]: files = ["file_0.csv", "file_1.csv", "file_2.csv"]

In [191]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

You can use the same approach to read all files matching a pattern. Here is an example using `glob`:

```
In [192]: import glob

In [193]: import os

In [194]: files = glob.glob("file_*.csv")

In [195]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

Finally, this strategy will work with the other `pd.read_*(...)` functions described in the *io docs*.

Parsing date components in multi-columns

Parsing date components in multi-columns is faster with a format

```
In [196]: i = pd.date_range("20000101", periods=10000)

In [197]: df = pd.DataFrame({"year": i.year, "month": i.month, "day": i.day})

In [198]: df.head()
Out[198]:
   year  month  day
0  2000      1    1
1  2000      1    2
2  2000      1    3
3  2000      1    4
4  2000      1    5

In [199]: %timeit pd.to_datetime(df.year * 10000 + df.month * 100 + df.day, format='%Y
↪%m%d')
   .....: ds = df.apply(lambda x: "%04d%02d%02d" % (x["year"], x["month"], x["day"]),␣
↪axis=1)
   .....: ds.head()
   .....: %timeit pd.to_datetime(ds)
   .....:
```

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```
3.75 ms +- 14.7 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
1.02 ms +- 12.8 us per loop (mean +- std. dev. of 7 runs, 1000 loops each)
```

Skip row between header and data

```
In [200]: data = """;;;;
   .....:  ;;;;
   .....:  ;;;;
   .....:  ;;;;
   .....:  ;;;;
   .....:  ;;;;
   .....: ;;;;
   .....:  ;;;;
   .....:  ;;;;
   .....: ;;;;
   .....: date;Param1;Param2;Param4;Param5
   .....:     ;m²;°C;m²;m
   .....: ;;;;
   .....: 01.01.1990 00:00;1;1;2;3
   .....: 01.01.1990 01:00;5;3;4;5
   .....: 01.01.1990 02:00;9;5;6;7
   .....: 01.01.1990 03:00;13;7;8;9
   .....: 01.01.1990 04:00;17;9;10;11
   .....: 01.01.1990 05:00;21;11;12;13
   .....: """
   .....:
```

Option 1: pass rows explicitly to skip rows

```
In [201]: from io import StringIO

In [202]: pd.read_csv(
   .....:     StringIO(data),
   .....:     sep=";",
   .....:     skiprows=[11, 12],
   .....:     index_col=0,
   .....:     parse_dates=True,
   .....:     header=10,
   .....: )
   .....:
Out[202]:
                     Param1  Param2  Param4  Param5
date
1990-01-01 00:00:00       1       1       2       3
1990-01-01 01:00:00       5       3       4       5
1990-01-01 02:00:00       9       5       6       7
1990-01-01 03:00:00      13       7       8       9
1990-01-01 04:00:00      17       9      10      11
1990-01-01 05:00:00      21      11      12      13
```

Option 2: read column names and then data

```
In [203]: pd.read_csv(StringIO(data), sep=";", header=10, nrows=10).columns
Out[203]: Index(['date', 'Param1', 'Param2', 'Param4', 'Param5'], dtype='object')

In [204]: columns = pd.read_csv(StringIO(data), sep=";", header=10, nrows=10).columns

In [205]: pd.read_csv(
   .....:     StringIO(data), sep=";", index_col=0, header=12, parse_dates=True,␣
↪names=columns
   .....: )
   .....:
Out[205]:
                     Param1  Param2  Param4  Param5
date
1990-01-01 00:00:00       1       1       2       3
1990-01-01 01:00:00       5       3       4       5
1990-01-01 02:00:00       9       5       6       7
1990-01-01 03:00:00      13       7       8       9
1990-01-01 04:00:00      17       9      10      11
1990-01-01 05:00:00      21      11      12      13
```

SQL

The *SQL* docs

Reading from databases with SQL

Excel

The *Excel* docs

Reading from a filelike handle

Modifying formatting in XlsxWriter output

HTML

Reading HTML tables from a server that cannot handle the default request header

HDFStore

The *HDFStores* docs

Simple queries with a Timestamp Index

Managing heterogeneous data using a linked multiple table hierarchy

Merging on-disk tables with millions of rows

Avoiding inconsistencies when writing to a store from multiple processes/threads

De-duplicating a large store by chunks, essentially a recursive reduction operation. Shows a function for taking in data from csv file and creating a store by chunks, with date parsing as well. See here

Creating a store chunk-by-chunk from a csv file

Appending to a store, while creating a unique index

Large Data work flows

Reading in a sequence of files, then providing a global unique index to a store while appending

Groupby on a HDFStore with low group density

Groupby on a HDFStore with high group density

Hierarchical queries on a HDFStore

Counting with a HDFStore

Troubleshoot HDFStore exceptions

Setting min_itemsize with strings

Using ptrepack to create a completely-sorted-index on a store

Storing Attributes to a group node

```
In [206]: df = pd.DataFrame(np.random.randn(8, 3))

In [207]: store = pd.HDFStore("test.h5")

In [208]: store.put("df", df)

# you can store an arbitrary Python object via pickle
In [209]: store.get_storer("df").attrs.my_attribute = {"A": 10}

In [210]: store.get_storer("df").attrs.my_attribute
Out[210]: {'A': 10}
```

You can create or load a HDFStore in-memory by passing the `driver` parameter to PyTables. Changes are only written to disk when the HDFStore is closed.

```
In [211]: store = pd.HDFStore("test.h5", "w", diver="H5FD_CORE")

In [212]: df = pd.DataFrame(np.random.randn(8, 3))

In [213]: store["test"] = df

# only after closing the store, data is written to disk:
In [214]: store.close()
```

Binary files

pandas readily accepts NumPy record arrays, if you need to read in a binary file consisting of an array of C structs. For example, given this C program in a file called `main.c` compiled with `gcc main.c -std=gnu99` on a 64-bit machine,

```
#include <stdio.h>
#include <stdint.h>

typedef struct _Data
{
    int32_t count;
    double avg;
    float scale;
```

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```
} Data;

int main(int argc, const char *argv[])
{
    size_t n = 10;
    Data d[n];

    for (int i = 0; i < n; ++i)
    {
        d[i].count = i;
        d[i].avg = i + 1.0;
        d[i].scale = (float) i + 2.0f;
    }

    FILE *file = fopen("binary.dat", "wb");
    fwrite(&d, sizeof(Data), n, file);
    fclose(file);

    return 0;
}
```

the following Python code will read the binary file `'binary.dat'` into a pandas `DataFrame`, where each element of the struct corresponds to a column in the frame:

```
names = "count", "avg", "scale"

# note that the offsets are larger than the size of the type because of
# struct padding
offsets = 0, 8, 16
formats = "i4", "f8", "f4"
dt = np.dtype({"names": names, "offsets": offsets, "formats": formats}, align=True)
df = pd.DataFrame(np.fromfile("binary.dat", dt))
```

Note: The offsets of the structure elements may be different depending on the architecture of the machine on which the file was created. Using a raw binary file format like this for general data storage is not recommended, as it is not cross platform. We recommended either HDF5 or parquet, both of which are supported by pandas' IO facilities.

2.27.10 Computation

Numerical integration (sample-based) of a time series

Correlation

Often it's useful to obtain the lower (or upper) triangular form of a correlation matrix calculated from *`DataFrame.corr()`*. This can be achieved by passing a boolean mask to `where` as follows:

```
In [215]: df = pd.DataFrame(np.random.random(size=(100, 5)))

In [216]: corr_mat = df.corr()

In [217]: mask = np.tril(np.ones_like(corr_mat, dtype=np.bool_), k=-1)
```

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```
In [218]: corr_mat.where(mask)
Out[218]:
          0         1         2         3   4
0       NaN       NaN       NaN       NaN NaN
1 -0.079861       NaN       NaN       NaN NaN
2 -0.236573  0.183801       NaN       NaN NaN
3 -0.013795 -0.051975  0.037235       NaN NaN
4 -0.031974  0.118342 -0.073499 -0.02063 NaN
```

The `method` argument within `DataFrame.corr` can accept a callable in addition to the named correlation types. Here we compute the `distance correlation <https://en.wikipedia.org/wiki/Distance_correlation>``__` matrix for a ``DataFrame` object.

```
In [219]: def distcorr(x, y):
   .....:     n = len(x)
   .....:     a = np.zeros(shape=(n, n))
   .....:     b = np.zeros(shape=(n, n))
   .....:     for i in range(n):
   .....:         for j in range(i + 1, n):
   .....:             a[i, j] = abs(x[i] - x[j])
   .....:             b[i, j] = abs(y[i] - y[j])
   .....:     a += a.T
   .....:     b += b.T
   .....:     a_bar = np.vstack([np.nanmean(a, axis=0)] * n)
   .....:     b_bar = np.vstack([np.nanmean(b, axis=0)] * n)
   .....:     A = a - a_bar - a_bar.T + np.full(shape=(n, n), fill_value=a_bar.mean())
   .....:     B = b - b_bar - b_bar.T + np.full(shape=(n, n), fill_value=b_bar.mean())
   .....:     cov_ab = np.sqrt(np.nansum(A * B)) / n
   .....:     std_a = np.sqrt(np.sqrt(np.nansum(A ** 2)) / n)
   .....:     std_b = np.sqrt(np.sqrt(np.nansum(B ** 2)) / n)
   .....:     return cov_ab / std_a / std_b
   .....:

In [220]: df = pd.DataFrame(np.random.normal(size=(100, 3)))

In [221]: df.corr(method=distcorr)
Out[221]:
          0         1         2
0  1.000000  0.197613  0.216328
1  0.197613  1.000000  0.208749
2  0.216328  0.208749  1.000000
```

2.27.11 Timedeltas

The *Timedeltas* docs.

Using timedeltas

```
In [222]: import datetime

In [223]: s = pd.Series(pd.date_range("2012-1-1", periods=3, freq="D"))

In [224]: s - s.max()
Out[224]:
0   -2 days
```

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```
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [225]: s.max() - s
Out[225]:
0   2 days
1   1 days
2   0 days
dtype: timedelta64[ns]

In [226]: s - datetime.datetime(2011, 1, 1, 3, 5)
Out[226]:
0   364 days 20:55:00
1   365 days 20:55:00
2   366 days 20:55:00
dtype: timedelta64[ns]

In [227]: s + datetime.timedelta(minutes=5)
Out[227]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [228]: datetime.datetime(2011, 1, 1, 3, 5) - s
Out[228]:
0   -365 days +03:05:00
1   -366 days +03:05:00
2   -367 days +03:05:00
dtype: timedelta64[ns]

In [229]: datetime.timedelta(minutes=5) + s
Out[229]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]
```

Adding and subtracting deltas and dates

```
In [230]: deltas = pd.Series([datetime.timedelta(days=i) for i in range(3)])

In [231]: df = pd.DataFrame({"A": s, "B": deltas})

In [232]: df
Out[232]:
           A      B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [233]: df["New Dates"] = df["A"] + df["B"]

In [234]: df["Delta"] = df["A"] - df["New Dates"]

In [235]: df
```

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```
Out[235]:
           A      B  New Dates   Delta
0 2012-01-01 0 days 2012-01-01  0 days
1 2012-01-02 1 days 2012-01-03 -1 days
2 2012-01-03 2 days 2012-01-05 -2 days

In [236]: df.dtypes
Out[236]:
A             datetime64[ns]
B            timedelta64[ns]
New Dates     datetime64[ns]
Delta        timedelta64[ns]
dtype: object
```

Another example

Values can be set to NaT using np.nan, similar to datetime

```
In [237]: y = s - s.shift()

In [238]: y
Out[238]:
0      NaT
1   1 days
2   1 days
dtype: timedelta64[ns]

In [239]: y[1] = np.nan

In [240]: y
Out[240]:
0      NaT
1      NaT
2   1 days
dtype: timedelta64[ns]
```

2.27.12 Creating example data

To create a dataframe from every combination of some given values, like R's `expand.grid()` function, we can create a dict where the keys are column names and the values are lists of the data values:

```
In [241]: def expand_grid(data_dict):
   .....:     rows = itertools.product(*data_dict.values())
   .....:     return pd.DataFrame.from_records(rows, columns=data_dict.keys())
   .....:

In [242]: df = expand_grid(
   .....:     {"height": [60, 70], "weight": [100, 140, 180], "sex": ["Male", "Female
↪"]}
   .....: )
   .....:

In [243]: df
Out[243]:
    height  weight     sex
```

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```
0        60     100    Male
1        60     100  Female
2        60     140    Male
3        60     140  Female
4        60     180    Male
5        60     180  Female
6        70     100    Male
7        70     100  Female
8        70     140    Male
9        70     140  Female
10       70     180    Male
11       70     180  Female
```

CHAPTER

THREE

API REFERENCE

This page gives an overview of all public pandas objects, functions and methods. All classes and functions exposed in `pandas.*` namespace are public.

Some subpackages are public which include `pandas.errors`, `pandas.plotting`, and `pandas.testing`. Public functions in `pandas.io` and `pandas.tseries` submodules are mentioned in the documentation. `pandas.api.types` subpackage holds some public functions related to data types in pandas.

Warning: The `pandas.core`, `pandas.compat`, and `pandas.util` top-level modules are PRIVATE. Stable functionality in such modules is not guaranteed.

3.1 Input/output

3.1.1 Pickling

read_pickle(filepath_or_buffer[, ...])	Load pickled pandas object (or any object) from file.

pandas.read_pickle

pandas.**read_pickle**(*filepath_or_buffer*, *compression='infer'*, *storage_options=None*)

Load pickled pandas object (or any object) from file.

Warning: Loading pickled data received from untrusted sources can be unsafe. See here.

Parameters

filepath_or_buffer [str, path object or file-like object] File path, URL, or buffer where the pickled object will be loaded from.

Changed in version 1.0.0: Accept URL. URL is not limited to S3 and GCS.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'] If 'infer' and 'path_or_url' is path-like, then detect compression from the following extensions: '.gz', '.bz2', '.zip', or '.xz' (otherwise no compression) If 'infer' and 'path_or_url' is not path-like, then use None (= no decompression).

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by

`fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

unpickled [same type as object stored in file]

See also:

DataFrame.to_pickle Pickle (serialize) DataFrame object to file.

Series.to_pickle Pickle (serialize) Series object to file.

read_hdf Read HDF5 file into a DataFrame.

read_sql Read SQL query or database table into a DataFrame.

read_parquet Load a parquet object, returning a DataFrame.

Notes

read_pickle is only guaranteed to be backwards compatible to pandas 0.20.3.

Examples

```
>>> original_df = pd.DataFrame({"foo": range(5), "bar": range(5, 10)})
>>> original_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
>>> pd.to_pickle(original_df, "./dummy.pkl")
```

```
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
```

```
>>> import os
>>> os.remove("./dummy.pkl")
```

3.1.2 Flat file

read_table(filepath_or_buffer[, sep, ...])	Read general delimited file into DataFrame.
read_csv(filepath_or_buffer[, sep, ...])	Read a comma-separated values (csv) file into DataFrame.
read_fwf(filepath_or_buffer[, colspecs, ...])	Read a table of fixed-width formatted lines into DataFrame.

pandas.read_table

pandas.**read_table**(*filepath_or_buffer*, *sep=<object object>*, *delimiter=None*, *header='infer'*, *names=None*, *index_col=None*, *usecols=None*, *squeeze=False*, *prefix=None*, *mangle_dupe_cols=True*, *dtype=None*, *engine=None*, *converters=None*, *true_values=None*, *false_values=None*, *skipinitialspace=False*, *skiprows=None*, *skipfooter=0*, *nrows=None*, *na_values=None*, *keep_default_na=True*, *na_filter=True*, *verbose=False*, *skip_blank_lines=True*, *parse_dates=False*, *infer_datetime_format=False*, *keep_date_col=False*, *date_parser=None*, *dayfirst=False*, *cache_dates=True*, *iterator=False*, *chunksize=None*, *compression='infer'*, *thousands=None*, *decimal='.'*, *lineterminator=None*, *quotechar='"'*, *quoting=0*, *doublequote=True*, *escapechar=None*, *comment=None*, *encoding=None*, *dialect=None*, *error_bad_lines=True*, *warn_bad_lines=True*, *delim_whitespace=False*, *low_memory=True*, *memory_map=False*, *float_precision=None*)

Read general delimited file into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for IO Tools.

Parameters

filepath_or_buffer [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.csv.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

sep [str, default '\t' (tab-stop)] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python's builtin sniffer tool, `csv.Sniffer`. In addition, separators longer than 1 character and different from `'\s+'` will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: `'\r\t'`.

delimiter [str, default `None`] Alias for sep.

header [int, list of int, default 'infer'] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this

parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

names [array-like, optional] List of column names to use. If the file contains a header row, then you should explicitly pass `header=0` to override the column names. Duplicates in this list are not allowed.

index_col [int, str, sequence of int / str, or False, default `None`] Column(s) to use as the row labels of the `DataFrame`, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.

Note: `index_col=False` can be used to force pandas to *not* use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

usecols [list-like or callable, optional] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in *names* or inferred from the document header row(s). For example, a valid list-like *usecols* parameter would be `[0, 1, 2]` or `['foo', 'bar', 'baz']`. Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`. To instantiate a DataFrame from `data` with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True. An example of a valid callable argument would be `lambda x: x.upper() in ['AAA', 'BBB', 'DDD']`. Using this parameter results in much faster parsing time and lower memory usage.

squeeze [bool, default False] If the parsed data only contains one column then return a Series.

prefix [str, optional] Prefix to add to column numbers when no header, e.g. 'X' for X0, X1, ...

mangle_dupe_cols [bool, default True] Duplicate columns will be specified as 'X', 'X.1', ...'X.N', rather than 'X'...'X'. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

dtype [Type name or dict of column -> type, optional] Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32, 'c': 'Int64'} Use *str* or *object* together with suitable *na_values* settings to preserve and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

engine [{'c', 'python'}, optional] Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

converters [dict, optional] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

true_values [list, optional] Values to consider as True.

false_values [list, optional] Values to consider as False.

skipinitialspace [bool, default False] Skip spaces after delimiter.

skiprows [list-like, int or callable, optional] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

skipfooter [int, default 0] Number of lines at bottom of file to skip (Unsupported with engine='c').

nrows [int, optional] Number of rows of file to read. Useful for reading pieces of large files.

na_values [scalar, str, list-like, or dict, optional] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: '', '#N/A', '#N/A N/A', '#NA', '-1.#IND', '-1.#QNAN', '-NaN', '-nan', '1.#IND', '1.#QNAN', '<NA>', 'N/A', 'NA', 'NULL', 'NaN', 'n/a', 'nan', 'null'.

keep_default_na [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether *na_values* is passed in, the behavior is as follows:

- If *keep_default_na* is True, and *na_values* are specified, *na_values* is appended to the default NaN values used for parsing.
- If *keep_default_na* is True, and *na_values* are not specified, only the default NaN values are used for parsing.
- If *keep_default_na* is False, and *na_values* are specified, only the NaN values specified *na_values* are used for parsing.
- If *keep_default_na* is False, and *na_values* are not specified, no strings will be parsed as NaN.

Note that if *na_filter* is passed in as False, the *keep_default_na* and *na_values* parameters will be ignored.

na_filter [bool, default True] Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file.

verbose [bool, default False] Indicate number of NA values placed in non-numeric columns.

skip_blank_lines [bool, default True] If True, skip over blank lines rather than interpreting as NaN values.

parse_dates [bool or list of int or names or list of lists or dict, default False] The behavior is as follows:

- boolean. If True -> try parsing the index.
- list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

If a column or index cannot be represented as an array of datetimes, say because of an unparsable value or a mixture of timezones, the column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`. To parse an index or column with a mixture of timezones, specify `date_parser` to be a partially-applied *`pandas.to_datetime()`* with `utc=True`. See *Parsing a CSV with mixed timezones* for more.

Note: A fast-path exists for iso8601-formatted dates.

infer_datetime_format [bool, default False] If True and *parse_dates* is enabled, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

keep_date_col [bool, default False] If True and *parse_dates* specifies combining multiple columns then keep the original columns.

date_parser [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call *date_parser* in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by *parse_dates*) as arguments; 2) concatenate (row-wise) the string values from the columns defined by *parse_dates* into a single array and pass that; and 3) call *date_parser* once for each row using one or more strings (corresponding to the columns defined by *parse_dates*) as arguments.

dayfirst [bool, default False] DD/MM format dates, international and European format.

cache_dates [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

iterator [bool, default False] Return TextFileReader object for iteration or getting chunks with `get_chunk()`.

Changed in version 1.2: `TextFileReader` is a context manager.

chunksize [int, optional] Return TextFileReader object for iteration. See the IO Tools docs for more information on `iterator` and `chunksize`.

Changed in version 1.2: `TextFileReader` is a context manager.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'] For on-the-fly decompression of on-disk data. If 'infer' and *filepath_or_buffer* is path-like, then detect compression from the following extensions: '.gz', '.bz2', '.zip', or '.xz' (otherwise no decompression). If using 'zip', the ZIP file must contain only one data file to be read in. Set to None for no decompression.

thousands [str, optional] Thousands separator.

decimal [str, default '.'] Character to recognize as decimal point (e.g. use ',' for European data).

lineterminator [str (length 1), optional] Character to break file into lines. Only valid with C parser.

quotechar [str (length 1), optional] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting [int or csv.QUOTE_* instance, default 0] Control field quoting behavior per `csv.QUOTE_*` constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

doublequote [bool, default `True`] When quotechar is specified and quoting is not `QUOTE_NONE`, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single `quotechar` element.

escapechar [str (length 1), optional] One-character string used to escape other characters.

comment [str, optional] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if `comment='#'`, parsing `#empty\na,b,c\n1,2,3` with `header=0` will result in 'a,b,c' being treated as the header.

encoding [str, optional] Encoding to use for UTF when reading/writing (ex. 'utf-8'). List of Python standard encodings . .. versionchanged:: 1.2

When `encoding` is `None`, `errors="replace"` is passed to `open()`. Otherwise, `errors="strict"` is passed to `open()`. This behavior was previously only the case for `engine="python"`.

dialect [str or csv.Dialect, optional] If provided, this parameter will override values (default or not) for the following parameters: *delimiter*, *doublequote*, *escapechar*, *skipinitialspace*, *quotechar*, and *quoting*. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

error_bad_lines [bool, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these "bad lines" will dropped from the DataFrame that is returned.

warn_bad_lines [bool, default True] If error_bad_lines is False, and warn_bad_lines is True, a warning for each "bad line" will be output.

delim_whitespace [bool, default False] Specifies whether or not whitespace (e.g. `' '` or `' '`) will be used as the sep. Equivalent to setting `sep='\s+'`. If this option is set to True, nothing should be passed in for the `delimiter` parameter.

low_memory [bool, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the *dtype* parameter. Note that the entire file is read into a single DataFrame regardless, use the *chunksize* or *iterator* parameter to return the data in chunks. (Only valid with C parser).

memory_map [bool, default False] If a filepath is provided for *filepath_or_buffer*, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

float_precision [str, optional] Specifies which converter the C engine should use for floating-point values. The options are `None` or 'high' for the ordinary converter, 'legacy' for the original lower precision pandas converter, and 'round_trip' for the round-trip converter.

Changed in version 1.2.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.

Returns

DataFrame or TextParser A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

See also:

DataFrame.to_csv Write DataFrame to a comma-separated values (csv) file.

read_csv Read a comma-separated values (csv) file into DataFrame.

read_fwf Read a table of fixed-width formatted lines into DataFrame.

Examples

```
>>> pd.read_table('data.csv')
```

pandas.read_csv

pandas.**read_csv**(*filepath_or_buffer*, *sep=<object object>*, *delimiter=None*, *header='infer'*, *names=None*, *index_col=None*, *usecols=None*, *squeeze=False*, *prefix=None*, *mangle_dupe_cols=True*, *dtype=None*, *engine=None*, *converters=None*, *true_values=None*, *false_values=None*, *skipinitialspace=False*, *skiprows=None*, *skipfooter=0*, *nrows=None*, *na_values=None*, *keep_default_na=True*, *na_filter=True*, *verbose=False*, *skip_blank_lines=True*, *parse_dates=False*, *infer_datetime_format=False*, *keep_date_col=False*, *date_parser=None*, *dayfirst=False*, *cache_dates=True*, *iterator=False*, *chunksize=None*, *compression='infer'*, *thousands=None*, *decimal='.'*, *lineterminator=None*, *quotechar='"'*, *quoting=0*, *doublequote=True*, *escapechar=None*, *comment=None*, *encoding=None*, *dialect=None*, *error_bad_lines=True*, *warn_bad_lines=True*, *delim_whitespace=False*, *low_memory=True*, *memory_map=False*, *float_precision=None*, *storage_options=None*)

Read a comma-separated values (csv) file into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for IO Tools.

Parameters

filepath_or_buffer [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.csv.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

sep [str, default ‘,’] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s builtin sniffer tool, `csv.Sniffer`. In addition, separators longer than 1 character and different from `'\s+'` will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: `'\r\t'`.

delimiter [str, default `None`] Alias for sep.

header [int, list of int, default ‘infer’] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

names [array-like, optional] List of column names to use. If the file contains a header row, then you should explicitly pass `header=0` to override the column names. Duplicates in this list are not allowed.

index_col [int, str, sequence of int / str, or False, default `None`] Column(s) to use as the row labels of the `DataFrame`, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.

Note: `index_col=False` can be used to force pandas to *not* use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

usecols [list-like or callable, optional] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in *names* or inferred from the document header row(s). For example, a valid list-like *usecols* parameter would be `[0, 1, 2]` or `['foo', 'bar', 'baz']`. Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`. To instantiate a DataFrame from `data` with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True. An example of a valid callable argument would be `lambda x: x.upper() in ['AAA', 'BBB', 'DDD']`. Using this parameter results in much faster parsing time and lower memory usage.

squeeze [bool, default False] If the parsed data only contains one column then return a Series.

prefix [str, optional] Prefix to add to column numbers when no header, e.g. 'X' for X0, X1, ...

mangle_dupe_cols [bool, default True] Duplicate columns will be specified as 'X', 'X.1', ...'X.N', rather than 'X'...'X'. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

dtype [Type name or dict of column -> type, optional] Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32, 'c': 'Int64'} Use *str* or *object* together with suitable *na_values* settings to preserve and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

engine [{'c', 'python'}, optional] Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

converters [dict, optional] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

true_values [list, optional] Values to consider as True.

false_values [list, optional] Values to consider as False.

skipinitialspace [bool, default False] Skip spaces after delimiter.

skiprows [list-like, int or callable, optional] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

skipfooter [int, default 0] Number of lines at bottom of file to skip (Unsupported with engine='c').

nrows [int, optional] Number of rows of file to read. Useful for reading pieces of large files.

na_values [scalar, str, list-like, or dict, optional] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted

as NaN: '', '#N/A', '#N/A N/A', '#NA', '-1.#IND', '-1.#QNAN', '-NaN', '-nan', '1.#IND', '1.#QNAN', '<NA>', 'N/A', 'NA', 'NULL', 'NaN', 'n/a', 'nan', 'null'.

keep_default_na [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether *na_values* is passed in, the behavior is as follows:

- If *keep_default_na* is True, and *na_values* are specified, *na_values* is appended to the default NaN values used for parsing.
- If *keep_default_na* is True, and *na_values* are not specified, only the default NaN values are used for parsing.
- If *keep_default_na* is False, and *na_values* are specified, only the NaN values specified *na_values* are used for parsing.
- If *keep_default_na* is False, and *na_values* are not specified, no strings will be parsed as NaN.

Note that if *na_filter* is passed in as False, the *keep_default_na* and *na_values* parameters will be ignored.

na_filter [bool, default True] Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file.

verbose [bool, default False] Indicate number of NA values placed in non-numeric columns.

skip_blank_lines [bool, default True] If True, skip over blank lines rather than interpreting as NaN values.

parse_dates [bool or list of int or names or list of lists or dict, default False] The behavior is as follows:

- boolean. If True -> try parsing the index.
- list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

If a column or index cannot be represented as an array of datetimes, say because of an unparsable value or a mixture of timezones, the column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`. To parse an index or column with a mixture of timezones, specify `date_parser` to be a partially-applied *`pandas.to_datetime()`* with `utc=True`. See *Parsing a CSV with mixed timezones* for more.

Note: A fast-path exists for iso8601-formatted dates.

infer_datetime_format [bool, default False] If True and *parse_dates* is enabled, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

keep_date_col [bool, default False] If True and *parse_dates* specifies combining multiple columns then keep the original columns.

date_parser [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call *date_parser* in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by *parse_dates*) as arguments;

2) concatenate (row-wise) the string values from the columns defined by *parse_dates* into a single array and pass that; and 3) call *date_parser* once for each row using one or more strings (corresponding to the columns defined by *parse_dates*) as arguments.

dayfirst [bool, default False] DD/MM format dates, international and European format.

cache_dates [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

iterator [bool, default False] Return TextFileReader object for iteration or getting chunks with `get_chunk()`.

Changed in version 1.2: `TextFileReader` is a context manager.

chunksize [int, optional] Return TextFileReader object for iteration. See the IO Tools docs for more information on `iterator` and `chunksize`.

Changed in version 1.2: `TextFileReader` is a context manager.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'] For on-the-fly decompression of on-disk data. If 'infer' and *filepath_or_buffer* is path-like, then detect compression from the following extensions: '.gz', '.bz2', '.zip', or '.xz' (otherwise no decompression). If using 'zip', the ZIP file must contain only one data file to be read in. Set to None for no decompression.

thousands [str, optional] Thousands separator.

decimal [str, default '.'] Character to recognize as decimal point (e.g. use ',' for European data).

lineterminator [str (length 1), optional] Character to break file into lines. Only valid with C parser.

quotechar [str (length 1), optional] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting [int or csv.QUOTE_* instance, default 0] Control field quoting behavior per `csv.QUOTE_*` constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

doublequote [bool, default `True`] When quotechar is specified and quoting is not `QUOTE_NONE`, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single `quotechar` element.

escapechar [str (length 1), optional] One-character string used to escape other characters.

comment [str, optional] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if `comment='#'`, parsing `#empty\na,b,c\n1,2,3` with `header=0` will result in 'a,b,c' being treated as the header.

encoding [str, optional] Encoding to use for UTF when reading/writing (ex. 'utf-8'). List of Python standard encodings . .. versionchanged:: 1.2

When `encoding` is `None`, `errors="replace"` is passed to `open()`. Otherwise, `errors="strict"` is passed to `open()`. This behavior was previously only the case for `engine="python"`.

dialect [str or csv.Dialect, optional] If provided, this parameter will override values (default or not) for the following parameters: *delimiter*, *doublequote*, *escapechar*, *skipinitialspace*, *quotechar*, and *quoting*. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

error_bad_lines [bool, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these "bad lines" will dropped from the DataFrame that is returned.

warn_bad_lines [bool, default True] If error_bad_lines is False, and warn_bad_lines is True, a warning for each "bad line" will be output.

delim_whitespace [bool, default False] Specifies whether or not whitespace (e.g. `' '` or `' '`) will be used as the sep. Equivalent to setting `sep='\s+'`. If this option is set to True, nothing should be passed in for the `delimiter` parameter.

low_memory [bool, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the *dtype* parameter. Note that the entire file is read into a single DataFrame regardless, use the *chunksize* or *iterator* parameter to return the data in chunks. (Only valid with C parser).

memory_map [bool, default False] If a filepath is provided for *filepath_or_buffer*, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

float_precision [str, optional] Specifies which converter the C engine should use for floating-point values. The options are `None` or 'high' for the ordinary converter, 'legacy' for the original lower precision pandas converter, and 'round_trip' for the round-trip converter.

Changed in version 1.2.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.

Returns

DataFrame or TextParser A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

See also:

DataFrame.to_csv Write DataFrame to a comma-separated values (csv) file.

read_csv Read a comma-separated values (csv) file into DataFrame.

read_fwf Read a table of fixed-width formatted lines into DataFrame.

Examples

```
>>> pd.read_csv('data.csv')
```

pandas.read_fwf

pandas.**read_fwf**(*filepath_or_buffer*, *colspecs='infer'*, *widths=None*, *infer_nrows=100*, ***kwds*)

Read a table of fixed-width formatted lines into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for IO Tools.

Parameters

filepath_or_buffer [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.csv`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

colspecs [list of tuple (int, int) or 'infer'. optional] A list of tuples giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[ ). String value 'infer' can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data which are not being skipped via skiprows (default='infer').

widths [list of int, optional] A list of field widths which can be used instead of 'colspecs' if the intervals are contiguous.

infer_nrows [int, default 100] The number of rows to consider when letting the parser determine the *colspecs*.

New in version 0.24.0.

****kwds** [optional] Optional keyword arguments can be passed to `TextFileReader`.

Returns

DataFrame or TextParser A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

See also:

DataFrame.to_csv Write DataFrame to a comma-separated values (csv) file.

read_csv Read a comma-separated values (csv) file into DataFrame.

Examples

```
>>> pd.read_fwf('data.csv')
```

3.1.3 Clipboard

read_clipboard([sep])	Read text from clipboard and pass to read_csv.

pandas.read_clipboard

pandas.**read_clipboard**(*sep='\\s+'*, ***kwargs*)

Read text from clipboard and pass to read_csv.

Parameters

sep [str, default 's+'] A string or regex delimiter. The default of 's+' denotes one or more whitespace characters.

****kwargs** See read_csv for the full argument list.

Returns

DataFrame A parsed DataFrame object.

3.1.4 Excel

read_excel(io[, sheet_name, header, names, ...])	Read an Excel file into a pandas DataFrame.
ExcelFile.parse([sheet_name, header, names, ...])	Parse specified sheet(s) into a DataFrame.

pandas.read_excel

pandas.**read_excel**(*io*, *sheet_name=0*, *header=0*, *names=None*, *index_col=None*, *usecols=None*, *squeeze=False*, *dtype=None*, *engine=None*, *converters=None*, *true_values=None*, *false_values=None*, *skiprows=None*, *nrows=None*, *na_values=None*, *keep_default_na=True*, *na_filter=True*, *verbose=False*, *parse_dates=False*, *date_parser=None*, *thousands=None*, *comment=None*, *skipfooter=0*, *convert_float=True*, *mangle_dupe_cols=True*, *storage_options=None*)

Read an Excel file into a pandas DataFrame.

Supports *xls*, *xlsx*, *xlsm*, *xlsb*, *odf*, *ods* and *odt* file extensions read from a local filesystem or URL. Supports an option to read a single sheet or a list of sheets.

Parameters

io [str, bytes, ExcelFile, xlrd.Book, path object, or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.xlsx`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

sheet_name [str, int, list, or None, default 0] Strings are used for sheet names. Integers are used in zero-indexed sheet positions. Lists of strings/integers are used to request multiple sheets. Specify None to get all sheets.

Available cases:

- Defaults to `0`: 1st sheet as a *DataFrame*
- `1`: 2nd sheet as a *DataFrame*
- `"Sheet1"`: Load sheet with name "Sheet1"
- `[0, 1, "Sheet5"]`: Load first, second and sheet named "Sheet5" as a dict of *DataFrame*
- None: All sheets.

header [int, list of int, default 0] Row (0-indexed) to use for the column labels of the parsed DataFrame. If a list of integers is passed those row positions will be combined into a `MultiIndex`. Use None if there is no header.

names [array-like, default None] List of column names to use. If file contains no header row, then you should explicitly pass header=None.

index_col [int, list of int, default None] Column (0-indexed) to use as the row labels of the DataFrame. Pass None if there is no such column. If a list is passed, those columns will be combined into a `MultiIndex`. If a subset of data is selected with `usecols`, index_col is based on the subset.

usecols [int, str, list-like, or callable default None]

- If None, then parse all columns.
- If str, then indicates comma separated list of Excel column letters and column ranges (e.g. "A:E" or "A,C,E:F"). Ranges are inclusive of both sides.
- If list of int, then indicates list of column numbers to be parsed.
- If list of string, then indicates list of column names to be parsed.

  New in version 0.24.0.

- If callable, then evaluate each column name against it and parse the column if the callable returns `True`.

Returns a subset of the columns according to behavior above.

New in version 0.24.0.

squeeze [bool, default False] If the parsed data only contains one column then return a Series.

dtype [Type name or dict of column -> type, default None] Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} Use *object* to preserve data as stored in Excel and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

engine [str, default None] If io is not a buffer or path, this must be set to identify io. Supported engines: "xlrd", "openpyxl", "odf", "pyxlsb". Engine compatibility :

- "xlrd" supports old-style Excel files (.xls).
- "openpyxl" supports newer Excel file formats.

- "odf" supports OpenDocument file formats (.odf, .ods, .odt).
- "pyxlsb" supports Binary Excel files.

Changed in version 1.2.0: The engine xlrd now only supports old-style `.xls` files. When `engine=None`, the following logic will be used to determine the engine:

- If `path_or_buffer` is an OpenDocument format (.odf, .ods, .odt), then odf will be used.
- Otherwise if `path_or_buffer` is an xls format, `xlrd` will be used.
- Otherwise if openpyxl is installed, then `openpyxl` will be used.
- Otherwise if `xlrd >= 2.0` is installed, a `ValueError` will be raised.
- Otherwise `xlrd` will be used and a `FutureWarning` will be raised. This case will raise a `ValueError` in a future version of pandas.

converters [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the Excel cell content, and return the transformed content.

true_values [list, default None] Values to consider as True.

false_values [list, default None] Values to consider as False.

skiprows [list-like, int, or callable, optional] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file. If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

nrows [int, default None] Number of rows to parse.

na_values [scalar, str, list-like, or dict, default None] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: '', '#N/A', '#N/A N/A', '#NA', '-1.#IND', '-1.#QNAN', '-NaN', '-nan', '1.#IND', '1.#QNAN', '<NA>', 'N/A', 'NA', 'NULL', 'NaN', 'n/a', 'nan', 'null'.

keep_default_na [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether *na_values* is passed in, the behavior is as follows:

- If *keep_default_na* is True, and *na_values* are specified, *na_values* is appended to the default NaN values used for parsing.
- If *keep_default_na* is True, and *na_values* are not specified, only the default NaN values are used for parsing.
- If *keep_default_na* is False, and *na_values* are specified, only the NaN values specified *na_values* are used for parsing.
- If *keep_default_na* is False, and *na_values* are not specified, no strings will be parsed as NaN.

Note that if *na_filter* is passed in as False, the *keep_default_na* and *na_values* parameters will be ignored.

na_filter [bool, default True] Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file.

verbose [bool, default False] Indicate number of NA values placed in non-numeric columns.

parse_dates [bool, list-like, or dict, default False] The behavior is as follows:

- bool. If True -> try parsing the index.
- list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

If a column or index contains an unparseable date, the entire column or index will be returned unaltered as an object data type. If you don`t want to parse some cells as date just change their type in Excel to "Text". For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_excel`.

Note: A fast-path exists for iso8601-formatted dates.

date_parser [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call *date_parser* in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by *parse_dates*) as arguments; 2) concatenate (row-wise) the string values from the columns defined by *parse_dates* into a single array and pass that; and 3) call *date_parser* once for each row using one or more strings (corresponding to the columns defined by *parse_dates*) as arguments.

thousands [str, default None] Thousands separator for parsing string columns to numeric. Note that this parameter is only necessary for columns stored as TEXT in Excel, any numeric columns will automatically be parsed, regardless of display format.

comment [str, default None] Comments out remainder of line. Pass a character or characters to this argument to indicate comments in the input file. Any data between the comment string and the end of the current line is ignored.

skipfooter [int, default 0] Rows at the end to skip (0-indexed).

convert_float [bool, default True] Convert integral floats to int (i.e., 1.0 –> 1). If False, all numeric data will be read in as floats: Excel stores all numbers as floats internally.

mangle_dupe_cols [bool, default True] Duplicate columns will be specified as 'X', 'X.1', ...'X.N', rather than 'X'...'X'. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a local path or a file-like buffer. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

DataFrame or dict of DataFrames DataFrame from the passed in Excel file. See notes in sheet_name argument for more information on when a dict of DataFrames is returned.

See also:

DataFrame.to_excel Write DataFrame to an Excel file.

DataFrame.to_csv Write DataFrame to a comma-separated values (csv) file.

read_csv Read a comma-separated values (csv) file into DataFrame.

read_fwf Read a table of fixed-width formatted lines into DataFrame.

Examples

The file can be read using the file name as string or an open file object:

```
>>> pd.read_excel('tmp.xlsx', index_col=0)
       Name  Value
0   string1      1
1   string2      2
2  #Comment      3
```

```
>>> pd.read_excel(open('tmp.xlsx', 'rb'),
...               sheet_name='Sheet3')
   Unnamed: 0      Name  Value
0           0   string1      1
1           1   string2      2
2           2  #Comment      3
```

Index and header can be specified via the *index_col* and *header* arguments

```
>>> pd.read_excel('tmp.xlsx', index_col=None, header=None)
     0         1      2
0  NaN      Name  Value
1  0.0   string1      1
2  1.0   string2      2
3  2.0  #Comment      3
```

Column types are inferred but can be explicitly specified

```
>>> pd.read_excel('tmp.xlsx', index_col=0,
...               dtype={'Name': str, 'Value': float})
       Name  Value
0   string1    1.0
1   string2    2.0
2  #Comment    3.0
```

True, False, and NA values, and thousands separators have defaults, but can be explicitly specified, too. Supply the values you would like as strings or lists of strings!

```
>>> pd.read_excel('tmp.xlsx', index_col=0,
...               na_values=['string1', 'string2'])
       Name  Value
0       NaN      1
1       NaN      2
2  #Comment      3
```

Comment lines in the excel input file can be skipped using the *comment* kwarg

```
>>> pd.read_excel('tmp.xlsx', index_col=0, comment='#')
      Name  Value
0  string1    1.0
1  string2    2.0
2     None    NaN
```

pandas.ExcelFile.parse

ExcelFile.**parse**(*sheet_name=0*, *header=0*, *names=None*, *index_col=None*, *usecols=None*, *squeeze=False*, *converters=None*, *true_values=None*, *false_values=None*, *skiprows=None*, *nrows=None*, *na_values=None*, *parse_dates=False*, *date_parser=None*, *thousands=None*, *comment=None*, *skipfooter=0*, *convert_float=True*, *mangle_dupe_cols=True*, ***kwds*)

Parse specified sheet(s) into a DataFrame.

Equivalent to read_excel(ExcelFile, ...) See the read_excel docstring for more info on accepted parameters.

Returns

DataFrame or dict of DataFrames DataFrame from the passed in Excel file.

ExcelWriter(path[, engine])	Class for writing DataFrame objects into excel sheets.

pandas.ExcelWriter

class pandas.**ExcelWriter**(*path*, *engine=None*, ***kwargs*)

Class for writing DataFrame objects into excel sheets.

Default is to use xlwt for xls, openpyxl for xlsx, odf for ods. See DataFrame.to_excel for typical usage.

The writer should be used as a context manager. Otherwise, call *close()* to save and close any opened file handles.

Parameters

path [str or typing.BinaryIO] Path to xls or xlsx or ods file.

engine [str (optional)] Engine to use for writing. If None, defaults to `io.excel.<extension>.writer`. NOTE: can only be passed as a keyword argument.

Deprecated since version 1.2.0: As the xlwt package is no longer maintained, the `xlwt` engine will be removed in a future version of pandas.

date_format [str, default None] Format string for dates written into Excel files (e.g. 'YYYY-MM-DD').

datetime_format [str, default None] Format string for datetime objects written into Excel files. (e.g. 'YYYY-MM-DD HH:MM:SS').

mode [{'w', 'a'}, default 'w'] File mode to use (write or append). Append does not work with fsspec URLs.

New in version 0.24.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://".

New in version 1.2.0.

Notes

None of the methods and properties are considered public.

For compatibility with CSV writers, ExcelWriter serializes lists and dicts to strings before writing.

Examples

Default usage:

```
>>> with ExcelWriter('path_to_file.xlsx') as writer:
...     df.to_excel(writer)
```

To write to separate sheets in a single file:

```
>>> with ExcelWriter('path_to_file.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet1')
...     df2.to_excel(writer, sheet_name='Sheet2')
```

You can set the date format or datetime format:

```
>>> with ExcelWriter('path_to_file.xlsx',
...                  date_format='YYYY-MM-DD',
...                  datetime_format='YYYY-MM-DD HH:MM:SS') as writer:
...     df.to_excel(writer)
```

You can also append to an existing Excel file:

```
>>> with ExcelWriter('path_to_file.xlsx', mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet3')
```

You can store Excel file in RAM:

```
>>> import io
>>> buffer = io.BytesIO()
>>> with pd.ExcelWriter(buffer) as writer:
...     df.to_excel(writer)
```

You can pack Excel file into zip archive:

```
>>> import zipfile
>>> with zipfile.ZipFile('path_to_file.zip', 'w') as zf:
...     with zf.open('filename.xlsx', 'w') as buffer:
...         with pd.ExcelWriter(buffer) as writer:
...             df.to_excel(writer)
```

Attributes

None	

Methods

None	

3.1.5 JSON

read_json([path_or_buf, orient, typ, dtype, ...])	Convert a JSON string to pandas object.
json_normalize(data[, record_path, meta, ...])	Normalize semi-structured JSON data into a flat table.

pandas.read_json

pandas.**read_json**(*path_or_buf=None*, *orient=None*, *typ='frame'*, *dtype=None*, *convert_axes=None*, *convert_dates=True*, *keep_default_dates=True*, *numpy=False*, *precise_float=False*, *date_unit=None*, *encoding=None*, *lines=False*, *chunksize=None*, *compression='infer'*, *nrows=None*, *storage_options=None*)

Convert a JSON string to pandas object.

Parameters

path_or_buf [a valid JSON str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.json`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

orient [str] Indication of expected JSON string format. Compatible JSON strings can be produced by `to_json()` with a corresponding orient value. The set of possible orients is:

- `'split'` : dict like `{index -> [index], columns -> [columns], data -> [values]}`
- `'records'` : list like `[{column -> value}, ... , {column -> value}]`
- `'index'` : dict like `{index -> {column -> value}}`
- `'columns'` : dict like `{column -> {index -> value}}`
- `'values'` : just the values array

The allowed and default values depend on the value of the *typ* parameter.

- when `typ == 'series'`,
  - allowed orients are `{'split','records','index'}`
  - default is `'index'`
  - The Series index must be unique for orient `'index'`.
- when `typ == 'frame'`,
  - allowed orients are `{'split','records','index', 'columns', 'values', 'table'}`

- default is 'columns'
- The DataFrame index must be unique for orients 'index' and 'columns'.
- The DataFrame columns must be unique for orients 'index', 'columns', and 'records'.

typ [{'frame', 'series'}, default 'frame'] The type of object to recover.

dtype [bool or dict, default None] If True, infer dtypes; if a dict of column to dtype, then use those; if False, then don't infer dtypes at all, applies only to the data.

For all orient values except 'table', default is True.

Changed in version 0.25.0: Not applicable for orient='table'.

convert_axes [bool, default None] Try to convert the axes to the proper dtypes.

For all orient values except 'table', default is True.

Changed in version 0.25.0: Not applicable for orient='table'.

convert_dates [bool or list of str, default True] If True then default datelike columns may be converted (depending on keep_default_dates). If False, no dates will be converted. If a list of column names, then those columns will be converted and default datelike columns may also be converted (depending on keep_default_dates).

keep_default_dates [bool, default True] If parsing dates (convert_dates is not False), then try to parse the default datelike columns. A column label is datelike if

- it ends with '_at',
- it ends with '_time',
- it begins with 'timestamp',
- it is 'modified', or
- it is 'date'.

numpy [bool, default False] Direct decoding to numpy arrays. Supports numeric data only, but non-numeric column and index labels are supported. Note also that the JSON ordering MUST be the same for each term if numpy=True.

Deprecated since version 1.0.0.

precise_float [bool, default False] Set to enable usage of higher precision (strtod) function when decoding string to double values. Default (False) is to use fast but less precise builtin functionality.

date_unit [str, default None] The timestamp unit to detect if converting dates. The default behaviour is to try and detect the correct precision, but if this is not desired then pass one of 's', 'ms', 'us' or 'ns' to force parsing only seconds, milliseconds, microseconds or nanoseconds respectively.

encoding [str, default is 'utf-8'] The encoding to use to decode py3 bytes.

lines [bool, default False] Read the file as a json object per line.

chunksize [int, optional] Return JsonReader object for iteration. See the line-delimited json docs for more information on chunksize. This can only be passed if *lines=True*. If this is None, the file will be read into memory all at once.

Changed in version 1.2: JsonReader is a context manager.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'] For on-the-fly decompression of on-disk data. If 'infer', then use gzip, bz2, zip or xz if path_or_buf is a string ending in '.gz', '.bz2', '.zip', or 'xz', respectively, and no decompression otherwise. If using 'zip', the ZIP file must contain only one data file to be read in. Set to None for no decompression.

nrows [int, optional] The number of lines from the line-delimited jsonfile that has to be read. This can only be passed if *lines=True*. If this is None, all the rows will be returned.

New in version 1.1.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

Series or DataFrame The type returned depends on the value of *typ*.

See also:

`DataFrame.to_json` Convert a DataFrame to a JSON string.

`Series.to_json` Convert a Series to a JSON string.

Notes

Specific to `orient='table'`, if a *`DataFrame`* with a literal *`Index`* name of *index* gets written with `to_json()`, the subsequent read operation will incorrectly set the *`Index`* name to `None`. This is because *index* is also used by *`DataFrame.to_json()`* to denote a missing *`Index`* name, and the subsequent *`read_json()`* operation cannot distinguish between the two. The same limitation is encountered with a *`MultiIndex`* and any names beginning with `'level_'`.

Examples

```
>>> df = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                   index=['row 1', 'row 2'],
...                   columns=['col 1', 'col 2'])
```

Encoding/decoding a Dataframe using `'split'` formatted JSON:

```
>>> df.to_json(orient='split')
'{"columns":["col 1","col 2"],
  "index":["row 1","row 2"],
  "data":[["a","b"],["c","d"]]}'
>>> pd.read_json(_, orient='split')
      col 1 col 2
row 1     a     b
row 2     c     d
```

Encoding/decoding a Dataframe using `'index'` formatted JSON:

```
>>> df.to_json(orient='index')
'{"row 1":{"col 1":"a","col 2":"b"},"row 2":{"col 1":"c","col 2":"d"}}'
>>> pd.read_json(_, orient='index')
      col 1 col 2
row 1     a     b
row 2     c     d
```

Encoding/decoding a Dataframe using `'records'` formatted JSON. Note that index labels are not preserved with this encoding.

```
>>> df.to_json(orient='records')
'[{"col 1":"a","col 2":"b"},{"col 1":"c","col 2":"d"}]'
>>> pd.read_json(_, orient='records')
  col 1 col 2
0     a     b
1     c     d
```

Encoding with Table Schema

```
>>> df.to_json(orient='table')
'{"schema": {"fields": [{"name": "index", "type": "string"},
                        {"name": "col 1", "type": "string"},
                        {"name": "col 2", "type": "string"}],
                "primaryKey": "index",
                "pandas_version": "0.20.0"},
    "data": [{"index": "row 1", "col 1": "a", "col 2": "b"},
             {"index": "row 2", "col 1": "c", "col 2": "d"}]}'
```

pandas.json_normalize

pandas.**json_normalize**(*data*, *record_path=None*, *meta=None*, *meta_prefix=None*, *record_prefix=None*, *errors='raise'*, *sep='.'*, *max_level=None*)

Normalize semi-structured JSON data into a flat table.

Parameters

data [dict or list of dicts] Unserialized JSON objects.

record_path [str or list of str, default None] Path in each object to list of records. If not passed, data will be assumed to be an array of records.

meta [list of paths (str or list of str), default None] Fields to use as metadata for each record in resulting table.

meta_prefix [str, default None] If True, prefix records with dotted (?) path, e.g. foo.bar.field if meta is [‘foo’, ‘bar’].

record_prefix [str, default None] If True, prefix records with dotted (?) path, e.g. foo.bar.field if path to records is [‘foo’, ‘bar’].

errors [{‘raise’, ‘ignore’}, default ‘raise’] Configures error handling.

- ‘ignore’ : will ignore KeyError if keys listed in meta are not always present.
- ‘raise’ : will raise KeyError if keys listed in meta are not always present.

sep [str, default ‘.’] Nested records will generate names separated by sep. e.g., for sep=’.’, {‘foo’: {‘bar’: 0}} -> foo.bar.

max_level [int, default None] Max number of levels(depth of dict) to normalize. if None, normalizes all levels.

New in version 0.25.0.

Returns

frame [DataFrame]

Normalize semi-structured JSON data into a flat table.

Examples

```
>>> data = [{'id': 1, 'name': {'first': 'Coleen', 'last': 'Volk'}},
...         {'name': {'given': 'Mose', 'family': 'Regner'}},
...         {'id': 2, 'name': 'Faye Raker'}]
>>> pd.json_normalize(data)
    id name.first name.last name.given name.family        name
0  1.0     Coleen      Volk        NaN         NaN         NaN
1  NaN        NaN       NaN       Mose      Regner         NaN
2  2.0        NaN       NaN        NaN         NaN  Faye Raker
```

```
>>> data = [{'id': 1,
...          'name': "Cole Volk",
...          'fitness': {'height': 130, 'weight': 60}},
...         {'name': "Mose Reg",
...          'fitness': {'height': 130, 'weight': 60}},
...         {'id': 2, 'name': 'Faye Raker',
...          'fitness': {'height': 130, 'weight': 60}}]
>>> pd.json_normalize(data, max_level=0)
    id        name                        fitness
0  1.0   Cole Volk  {'height': 130, 'weight': 60}
1  NaN    Mose Reg  {'height': 130, 'weight': 60}
2  2.0  Faye Raker  {'height': 130, 'weight': 60}
```

Normalizes nested data up to level 1.

```
>>> data = [{'id': 1,
...          'name': "Cole Volk",
...          'fitness': {'height': 130, 'weight': 60}},
...         {'name': "Mose Reg",
...          'fitness': {'height': 130, 'weight': 60}},
...         {'id': 2, 'name': 'Faye Raker',
...          'fitness': {'height': 130, 'weight': 60}}]
>>> pd.json_normalize(data, max_level=1)
    id        name  fitness.height  fitness.weight
0  1.0   Cole Volk             130              60
1  NaN    Mose Reg             130              60
2  2.0  Faye Raker             130              60
```

```
>>> data = [{'state': 'Florida',
...          'shortname': 'FL',
...          'info': {'governor': 'Rick Scott'},
...          'counties': [{'name': 'Dade', 'population': 12345},
...                       {'name': 'Broward', 'population': 40000},
...                       {'name': 'Palm Beach', 'population': 60000}]},
...         {'state': 'Ohio',
```

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```
...          'shortname': 'OH',
...          'info': {'governor': 'John Kasich'},
...          'counties': [{'name': 'Summit', 'population': 1234},
...                       {'name': 'Cuyahoga', 'population': 1337}]}]
>>> result = pd.json_normalize(data, 'counties', ['state', 'shortname',
...                                               ['info', 'governor']])
>>> result
         name  population    state shortname info.governor
0        Dade       12345   Florida    FL    Rick Scott
1     Broward       40000   Florida    FL    Rick Scott
2  Palm Beach       60000   Florida    FL    Rick Scott
3      Summit        1234   Ohio       OH    John Kasich
4    Cuyahoga        1337   Ohio       OH    John Kasich
```

```
>>> data = {'A': [1, 2]}
>>> pd.json_normalize(data, 'A', record_prefix='Prefix.')
    Prefix.0
0          1
1          2
```

Returns normalized data with columns prefixed with the given string.

build_table_schema(data[, index, ...])	Create a Table schema from `data`.

pandas.io.json.build_table_schema

pandas.io.json.**build_table_schema**(*data*, *index=True*, *primary_key=None*, *version=True*)

Create a Table schema from `data`.

Parameters

data [Series, DataFrame]

index [bool, default True] Whether to include `data.index` in the schema.

primary_key [bool or None, default True] Column names to designate as the primary key. The default *None* will set *'primaryKey'* to the index level or levels if the index is unique.

version [bool, default True] Whether to include a field *pandas_version* with the version of pandas that generated the schema.

Returns

schema [dict]

Notes

See Table Schema for conversion types. Timedeltas as converted to ISO8601 duration format with 9 decimal places after the seconds field for nanosecond precision.

Categoricals are converted to the *any* dtype, and use the *enum* field constraint to list the allowed values. The *ordered* attribute is included in an *ordered* field.

Examples

```
>>> df = pd.DataFrame(
...     {'A': [1, 2, 3],
...      'B': ['a', 'b', 'c'],
...      'C': pd.date_range('2016-01-01', freq='d', periods=3),
...     }, index=pd.Index(range(3), name='idx'))
>>> build_table_schema(df)
{'fields': [{'name': 'idx', 'type': 'integer'},
{'name': 'A', 'type': 'integer'},
{'name': 'B', 'type': 'string'},
{'name': 'C', 'type': 'datetime'}],
'pandas_version': '0.20.0',
'primaryKey': ['idx']}
```

3.1.6 HTML

read_html(io[, match, flavor, header, ...])	Read HTML tables into a `list` of `DataFrame` objects.

pandas.read_html

pandas.**read_html**(*io*, *match='.+'*, *flavor=None*, *header=None*, *index_col=None*, *skiprows=None*, *attrs=None*, *parse_dates=False*, *thousands=','*, *encoding=None*, *decimal='.'*, *converters=None*, *na_values=None*, *keep_default_na=True*, *displayed_only=True*)

Read HTML tables into a `list` of `DataFrame` objects.

Parameters

io [str, path object or file-like object] A URL, a file-like object, or a raw string containing HTML. Note that lxml only accepts the http, ftp and file url protocols. If you have a URL that starts with `'https'` you might try removing the `'s'`.

match [str or compiled regular expression, optional] The set of tables containing text matching this regex or string will be returned. Unless the HTML is extremely simple you will probably need to pass a non-empty string here. Defaults to '.+' (match any non-empty string). The default value will return all tables contained on a page. This value is converted to a regular expression so that there is consistent behavior between Beautiful Soup and lxml.

flavor [str, optional] The parsing engine to use. 'bs4' and 'html5lib' are synonymous with each other, they are both there for backwards compatibility. The default of `None` tries to use `lxml` to parse and if that fails it falls back on `bs4` + `html5lib`.

header [int or list-like, optional] The row (or list of rows for a *MultiIndex*) to use to make the columns headers.

index_col [int or list-like, optional] The column (or list of columns) to use to create the index.

skiprows [int, list-like or slice, optional] Number of rows to skip after parsing the column integer. 0-based. If a sequence of integers or a slice is given, will skip the rows indexed by that sequence. Note that a single element sequence means 'skip the nth row' whereas an integer means 'skip n rows'.

attrs [dict, optional] This is a dictionary of attributes that you can pass to use to identify the table in the HTML. These are not checked for validity before being passed to lxml or Beautiful

Soup. However, these attributes must be valid HTML table attributes to work correctly. For example,

```
attrs = {'id': 'table'}
```

is a valid attribute dictionary because the 'id' HTML tag attribute is a valid HTML attribute for *any* HTML tag as per this document.

```
attrs = {'asdf': 'table'}
```

is *not* a valid attribute dictionary because 'asdf' is not a valid HTML attribute even if it is a valid XML attribute. Valid HTML 4.01 table attributes can be found here. A working draft of the HTML 5 spec can be found here. It contains the latest information on table attributes for the modern web.

parse_dates [bool, optional] See *read_csv()* for more details.

thousands [str, optional] Separator to use to parse thousands. Defaults to `','`.

encoding [str, optional] The encoding used to decode the web page. Defaults to `None`.``None`` preserves the previous encoding behavior, which depends on the underlying parser library (e.g., the parser library will try to use the encoding provided by the document).

decimal [str, default '.'] Character to recognize as decimal point (e.g. use ',' for European data).

converters [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the cell (not column) content, and return the transformed content.

na_values [iterable, default None] Custom NA values.

keep_default_na [bool, default True] If na_values are specified and keep_default_na is False the default NaN values are overridden, otherwise they're appended to.

displayed_only [bool, default True] Whether elements with "display: none" should be parsed.

Returns

dfs A list of DataFrames.

See also:

read_csv Read a comma-separated values (csv) file into DataFrame.

Notes

Before using this function you should read the *gotchas about the HTML parsing libraries*.

Expect to do some cleanup after you call this function. For example, you might need to manually assign column names if the column names are converted to NaN when you pass the *header=0* argument. We try to assume as little as possible about the structure of the table and push the idiosyncrasies of the HTML contained in the table to the user.

This function searches for `<table>` elements and only for `<tr>` and `<th>` rows and `<td>` elements within each `<tr>` or `<th>` element in the table. `<td>` stands for "table data". This function attempts to properly handle `colspan` and `rowspan` attributes. If the function has a `<thead>` argument, it is used to construct the header, otherwise the function attempts to find the header within the body (by putting rows with only `<th>` elements into the header).

Similar to *read_csv()* the *header* argument is applied **after** *skiprows* is applied.

This function will *always* return a list of `DataFrame` *or* it will fail, e.g., it will *not* return an empty list.

Examples

See the *read_html documentation in the IO section of the docs* for some examples of reading in HTML tables.

3.1.7 HDFStore: PyTables (HDF5)

`read_hdf`(path_or_buf[, key, mode, errors, ...])	Read from the store, close it if we opened it.
`HDFStore.put`(key, value[, format, index, ...])	Store object in HDFStore.
`HDFStore.append`(key, value[, format, axes, ...])	Append to Table in file.
`HDFStore.get`(key)	Retrieve pandas object stored in file.
`HDFStore.select`(key[, where, start, stop, ...])	Retrieve pandas object stored in file, optionally based on where criteria.
`HDFStore.info`()	Print detailed information on the store.
`HDFStore.keys`([include])	Return a list of keys corresponding to objects stored in HDFStore.
`HDFStore.groups`()	Return a list of all the top-level nodes.
`HDFStore.walk`([where])	Walk the pytables group hierarchy for pandas objects.

pandas.read_hdf

pandas.**read_hdf**(*path_or_buf*, *key=None*, *mode='r'*, *errors='strict'*, *where=None*, *start=None*, *stop=None*, *columns=None*, *iterator=False*, *chunksize=None*, ***kwargs*)

Read from the store, close it if we opened it.

Retrieve pandas object stored in file, optionally based on where criteria.

Warning: Pandas uses PyTables for reading and writing HDF5 files, which allows serializing object-dtype data with pickle when using the "fixed" format. Loading pickled data received from untrusted sources can be unsafe.

See: https://docs.python.org/3/library/pickle.html for more.

Parameters

path_or_buf [str, path object, pandas.HDFStore or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.h5`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

Alternatively, pandas accepts an open `pandas.HDFStore` object.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

key [object, optional] The group identifier in the store. Can be omitted if the HDF file contains a single pandas object.

mode [{'r', 'r+', 'a'}, default 'r'] Mode to use when opening the file. Ignored if path_or_buf is a `pandas.HDFStore`. Default is 'r'.

errors [str, default 'strict'] Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.

where [list, optional] A list of Term (or convertible) objects.

start [int, optional] Row number to start selection.

stop [int, optional] Row number to stop selection.

columns [list, optional] A list of columns names to return.

iterator [bool, optional] Return an iterator object.

chunksize [int, optional] Number of rows to include in an iteration when using an iterator.

****kwargs** Additional keyword arguments passed to HDFStore.

Returns

item [object] The selected object. Return type depends on the object stored.

See also:

DataFrame.to_hdf Write a HDF file from a DataFrame.

HDFStore Low-level access to HDF files.

Examples

```
>>> df = pd.DataFrame([[1, 1.0, 'a']], columns=['x', 'y', 'z'])
>>> df.to_hdf('./store.h5', 'data')
>>> reread = pd.read_hdf('./store.h5')
```

pandas.HDFStore.put

HDFStore.**put**(*key*, *value*, *format=None*, *index=True*, *append=False*, *complib=None*, *complevel=None*, *min_itemsize=None*, *nan_rep=None*, *data_columns=None*, *encoding=None*, *errors='strict'*, *track_times=True*, *dropna=False*)

Store object in HDFStore.

Parameters

key [str]

value [{Series, DataFrame}]

format ['fixed(f)|table(t)', default is 'fixed'] Format to use when storing object in HDFStore. Value can be one of:

'fixed' Fixed format. Fast writing/reading. Not-appendable, nor searchable.

'table' Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.

append [bool, default False] This will force Table format, append the input data to the existing.

data_columns [list, default None] List of columns to create as data columns, or True to use all columns. See here.

encoding [str, default None] Provide an encoding for strings.

track_times [bool, default True] Parameter is propagated to 'create_table' method of 'PyTables'. If set to False it enables to have the same h5 files (same hashes) independent on creation time.

New in version 1.1.0.

pandas.HDFStore.append

HDFStore.**append**(*key*, *value*, *format=None*, *axes=None*, *index=True*, *append=True*, *complib=None*, *complevel=None*, *columns=None*, *min_itemsize=None*, *nan_rep=None*, *chunksize=None*, *expectedrows=None*, *dropna=None*, *data_columns=None*, *encoding=None*, *errors='strict'*)

Append to Table in file. Node must already exist and be Table format.

Parameters

key [str]

value [{Series, DataFrame}]

format ['table' is the default] Format to use when storing object in HDFStore. Value can be one of:

'table' Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.

append [bool, default True] Append the input data to the existing.

data_columns [list of columns, or True, default None] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See here.

min_itemsize [dict of columns that specify minimum str sizes]

nan_rep [str to use as str nan representation]

chunksize [size to chunk the writing]

expectedrows [expected TOTAL row size of this table]

encoding [default None, provide an encoding for str]

dropna [bool, default False] Do not write an ALL nan row to the store settable by the option 'io.hdf.dropna_table'.

Notes

Does *not* check if data being appended overlaps with existing data in the table, so be careful

pandas.HDFStore.get

HDFStore.**get**(*key*)

Retrieve pandas object stored in file.

Parameters

key [str]

Returns

object Same type as object stored in file.

pandas.HDFStore.select

HDFStore.**select**(*key*, *where=None*, *start=None*, *stop=None*, *columns=None*, *iterator=False*, *chunksize=None*, *auto_close=False*)

Retrieve pandas object stored in file, optionally based on where criteria.

> **Warning:** Pandas uses PyTables for reading and writing HDF5 files, which allows serializing object-dtype data with pickle when using the "fixed" format. Loading pickled data received from untrusted sources can be unsafe.
>
> See: https://docs.python.org/3/library/pickle.html for more.

Parameters

key [str] Object being retrieved from file.

where [list or None] List of Term (or convertible) objects, optional.

start [int or None] Row number to start selection.

stop [int, default None] Row number to stop selection.

columns [list or None] A list of columns that if not None, will limit the return columns.

iterator [bool or False] Returns an iterator.

chunksize [int or None] Number or rows to include in iteration, return an iterator.

auto_close [bool or False] Should automatically close the store when finished.

Returns

object Retrieved object from file.

pandas.HDFStore.info

HDFStore.**info**()

Print detailed information on the store.

Returns

str

pandas.HDFStore.keys

HDFStore.**keys**(*include='pandas'*)

Return a list of keys corresponding to objects stored in HDFStore.

Parameters

include [str, default 'pandas'] When kind equals 'pandas' return pandas objects. When kind equals 'native' return native HDF5 Table objects.

New in version 1.1.0.

Returns

list List of ABSOLUTE path-names (e.g. have the leading '/').

Raises

raises ValueError if kind has an illegal value

pandas.HDFStore.groups

HDFStore.**groups**()

Return a list of all the top-level nodes.

Each node returned is not a pandas storage object.

Returns

list List of objects.

pandas.HDFStore.walk

HDFStore.**walk**(*where='/'*)

Walk the pytables group hierarchy for pandas objects.

This generator will yield the group path, subgroups and pandas object names for each group.

Any non-pandas PyTables objects that are not a group will be ignored.

The *where* group itself is listed first (preorder), then each of its child groups (following an alphanumerical order) is also traversed, following the same procedure.

New in version 0.24.0.

Parameters

where [str, default "/"] Group where to start walking.

Yields

path [str] Full path to a group (without trailing '/').

groups [list] Names (strings) of the groups contained in *path*.

leaves [list] Names (strings) of the pandas objects contained in *path*.

3.1.8 Feather

read_feather(path[, columns, use_threads, ...])	Load a feather-format object from the file path.

pandas.read_feather

pandas.**read_feather**(*path*, *columns=None*, *use_threads=True*, *storage_options=None*)

Load a feather-format object from the file path.

Parameters

path [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.feather`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

columns [sequence, default None] If not provided, all columns are read.

New in version 0.24.0.

use_threads [bool, default True]

Whether to parallelize reading using multiple threads.

New in version 0.24.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

type of object stored in file

3.1.9 Parquet

`read_parquet`(path[, engine, columns, ...])	Load a parquet object from the file path, returning a DataFrame.

pandas.read_parquet

pandas.**read_parquet**(*path*, *engine='auto'*, *columns=None*, *use_nullable_dtypes=False*, ***kwargs*)

Load a parquet object from the file path, returning a DataFrame.

Parameters

path [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.parquet`. A file URL can also be a path to a directory that contains multiple partitioned parquet files. Both pyarrow and fastparquet support paths to directories as well as file URLs. A directory path could be: `file://localhost/path/to/tables` or `s3://bucket/partition_dir`

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

engine [{'auto', 'pyarrow', 'fastparquet'}, default 'auto'] Parquet library to use. If 'auto', then the option `io.parquet.engine` is used. The default `io.parquet.engine` behavior is to try 'pyarrow', falling back to 'fastparquet' if 'pyarrow' is unavailable.

columns [list, default=None] If not None, only these columns will be read from the file.

use_nullable_dtypes [bool, default False] If True, use dtypes that use `pd.NA` as missing value indicator for the resulting DataFrame (only applicable for `engine="pyarrow"`). As new dtypes are added that support `pd.NA` in the future, the output with this option will change to use those dtypes. Note: this is an experimental option, and behaviour (e.g. additional support dtypes) may change without notice.

New in version 1.2.0.

****kwargs** Any additional kwargs are passed to the engine.

Returns

DataFrame

3.1.10 ORC

read_orc(path[, columns])	Load an ORC object from the file path, returning a DataFrame.

pandas.read_orc

pandas.**read_orc**(*path*, *columns=None*, ***kwargs*)

Load an ORC object from the file path, returning a DataFrame.

New in version 1.0.0.

Parameters

path [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.orc`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

columns [list, default None] If not None, only these columns will be read from the file.

****kwargs** Any additional kwargs are passed to pyarrow.

Returns

DataFrame

3.1.11 SAS

read_sas(filepath_or_buffer[, format, ...])	Read SAS files stored as either XPORT or SAS7BDAT format files.

pandas.read_sas

pandas.**read_sas**(*filepath_or_buffer*, *format=None*, *index=None*, *encoding=None*, *chunksize=None*, *iterator=False*)

Read SAS files stored as either XPORT or SAS7BDAT format files.

Parameters

filepath_or_buffer [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.sas`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

format [str {'xport', 'sas7bdat'} or None] If None, file format is inferred from file extension. If 'xport' or 'sas7bdat', uses the corresponding format.

index [identifier of index column, defaults to None] Identifier of column that should be used as index of the DataFrame.

encoding [str, default is None] Encoding for text data. If None, text data are stored as raw bytes.

chunksize [int] Read file *chunksize* lines at a time, returns iterator.

Changed in version 1.2: `TextFileReader` is a context manager.

iterator [bool, defaults to False] If True, returns an iterator for reading the file incrementally.

Changed in version 1.2: `TextFileReader` is a context manager.

Returns

DataFrame if iterator=False and chunksize=None, else SAS7BDATReader

or XportReader

3.1.12 SPSS

read_spss(path[, usecols, convert_categoricals])	Load an SPSS file from the file path, returning a DataFrame.

pandas.read_spss

pandas.**read_spss**(*path*, *usecols=None*, *convert_categoricals=True*)

Load an SPSS file from the file path, returning a DataFrame.

New in version 0.25.0.

Parameters

path [str or Path] File path.

usecols [list-like, optional] Return a subset of the columns. If None, return all columns.

convert_categoricals [bool, default is True] Convert categorical columns into pd.Categorical.

Returns

DataFrame

3.1.13 SQL

read_sql_table(table_name, con[, schema, ...])	Read SQL database table into a DataFrame.
read_sql_query(sql, con[, index_col, ...])	Read SQL query into a DataFrame.
read_sql(sql, con[, index_col, ...])	Read SQL query or database table into a DataFrame.

pandas.read_sql_table

pandas.**read_sql_table**(*table_name*, *con*, *schema=None*, *index_col=None*, *coerce_float=True*, *parse_dates=None*, *columns=None*, *chunksize=None*)

Read SQL database table into a DataFrame.

Given a table name and a SQLAlchemy connectable, returns a DataFrame. This function does not support DBAPI connections.

Parameters

table_name [str] Name of SQL table in database.

con [SQLAlchemy connectable or str] A database URI could be provided as str. SQLite DBAPI connection mode not supported.

schema [str, default None] Name of SQL schema in database to query (if database flavor supports this). Uses default schema if None (default).

index_col [str or list of str, optional, default: None] Column(s) to set as index(MultiIndex).

coerce_float [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point. Can result in loss of Precision.

parse_dates [list or dict, default None]

- List of column names to parse as dates.
- Dict of `{column_name: format string}` where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
- Dict of `{column_name: arg dict}`, where the arg dict corresponds to the keyword arguments of *pandas.to_datetime()* Especially useful with databases without native Datetime support, such as SQLite.

columns [list, default None] List of column names to select from SQL table.

chunksize [int, default None] If specified, returns an iterator where *chunksize* is the number of rows to include in each chunk.

Returns

DataFrame or Iterator[DataFrame] A SQL table is returned as two-dimensional data structure with labeled axes.

See also:

read_sql_query Read SQL query into a DataFrame.

read_sql Read SQL query or database table into a DataFrame.

Notes

Any datetime values with time zone information will be converted to UTC.

Examples

```
>>> pd.read_sql_table('table_name', 'postgres:///db_name')
```

pandas.read_sql_query

pandas.**read_sql_query**(*sql*, *con*, *index_col=None*, *coerce_float=True*, *params=None*, *parse_dates=None*, *chunksize=None*)

Read SQL query into a DataFrame.

Returns a DataFrame corresponding to the result set of the query string. Optionally provide an *index_col* parameter to use one of the columns as the index, otherwise default integer index will be used.

Parameters

sql [str SQL query or SQLAlchemy Selectable (select or text object)] SQL query to be executed.

con [SQLAlchemy connectable, str, or sqlite3 connection] Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col [str or list of str, optional, default: None] Column(s) to set as index(MultiIndex).

coerce_float [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point. Useful for SQL result sets.

params [list, tuple or dict, optional, default: None] List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name' : 'value'}.

parse_dates [list or dict, default: None]

- List of column names to parse as dates.
- Dict of `{column_name: format string}` where format string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
- Dict of `{column_name: arg dict}`, where the arg dict corresponds to the keyword arguments of *pandas.to_datetime()* Especially useful with databases without native Datetime support, such as SQLite.

chunksize [int, default None] If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns

DataFrame or Iterator[DataFrame]

See also:

read_sql_table Read SQL database table into a DataFrame.

read_sql Read SQL query or database table into a DataFrame.

Notes

Any datetime values with time zone information parsed via the *parse_dates* parameter will be converted to UTC.

pandas.read_sql

pandas.**read_sql**(*sql*, *con*, *index_col=None*, *coerce_float=True*, *params=None*, *parse_dates=None*, *columns=None*, *chunksize=None*)

Read SQL query or database table into a DataFrame.

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (for backward compatibility). It will delegate to the specific function depending on the provided input. A SQL query will be routed to `read_sql_query`, while a database table name will be routed to `read_sql_table`. Note that the delegated function might have more specific notes about their functionality not listed here.

Parameters

sql [str or SQLAlchemy Selectable (select or text object)] SQL query to be executed or a table name.

con [SQLAlchemy connectable, str, or sqlite3 connection] Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable; str connections are closed automatically. See here.

index_col [str or list of str, optional, default: None] Column(s) to set as index(MultiIndex).

coerce_float [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets.

params [list, tuple or dict, optional, default: None] List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name' : 'value'}.

parse_dates [list or dict, default: None]

- List of column names to parse as dates.
- Dict of `{column_name: format string}` where format string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
- Dict of `{column_name: arg dict}`, where the arg dict corresponds to the keyword arguments of *pandas.to_datetime()* Especially useful with databases without native Datetime support, such as SQLite.

columns [list, default: None] List of column names to select from SQL table (only used when reading a table).

chunksize [int, default None] If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns

DataFrame or Iterator[DataFrame]

See also:

read_sql_table Read SQL database table into a DataFrame.

read_sql_query	Read SQL query into a DataFrame.

3.1.14 Google BigQuery

read_gbq(query[, project_id, index_col, ...])	Load data from Google BigQuery.

pandas.read_gbq

pandas.**read_gbq**(*query*, *project_id=None*, *index_col=None*, *col_order=None*, *reauth=False*, *auth_local_webserver=False*, *dialect=None*, *location=None*, *configuration=None*, *credentials=None*, *use_bqstorage_api=None*, *max_results=None*, *progress_bar_type=None*)

Load data from Google BigQuery.

This function requires the pandas-gbq package.

See the How to authenticate with Google BigQuery guide for authentication instructions.

Parameters

query [str] SQL-Like Query to return data values.

project_id [str, optional] Google BigQuery Account project ID. Optional when available from the environment.

index_col [str, optional] Name of result column to use for index in results DataFrame.

col_order [list(str), optional] List of BigQuery column names in the desired order for results DataFrame.

reauth [bool, default False] Force Google BigQuery to re-authenticate the user. This is useful if multiple accounts are used.

auth_local_webserver [bool, default False] Use the local webserver flow instead of the console flow when getting user credentials.

New in version 0.2.0 of pandas-gbq.

dialect [str, default 'legacy'] Note: The default value is changing to 'standard' in a future version.

SQL syntax dialect to use. Value can be one of:

'legacy' Use BigQuery's legacy SQL dialect. For more information see BigQuery Legacy SQL Reference.

'standard' Use BigQuery's standard SQL, which is compliant with the SQL 2011 standard. For more information see BigQuery Standard SQL Reference.

Changed in version 0.24.0.

location [str, optional] Location where the query job should run. See the BigQuery locations documentation for a list of available locations. The location must match that of any datasets used in the query.

New in version 0.5.0 of pandas-gbq.

configuration [dict, optional] Query config parameters for job processing. For example:

configuration = {'query': {'useQueryCache': False}}

For more information see BigQuery REST API Reference.

credentials [google.auth.credentials.Credentials, optional] Credentials for accessing Google APIs. Use this parameter to override default credentials, such as to use Compute Engine `google.auth.compute_engine.Credentials` or Service Account `google.oauth2.service_account.Credentials` directly.

New in version 0.8.0 of pandas-gbq.

New in version 0.24.0.

use_bqstorage_api [bool, default False] Use the BigQuery Storage API to download query results quickly, but at an increased cost. To use this API, first enable it in the Cloud Console. You must also have the bigquery.readsessions.create permission on the project you are billing queries to.

This feature requires version 0.10.0 or later of the `pandas-gbq` package. It also requires the `google-cloud-bigquery-storage` and `fastavro` packages.

New in version 0.25.0.

max_results [int, optional] If set, limit the maximum number of rows to fetch from the query results.

New in version 0.12.0 of pandas-gbq.

New in version 1.1.0.

progress_bar_type [Optional, str] If set, use the tqdm library to display a progress bar while the data downloads. Install the `tqdm` package to use this feature.

Possible values of `progress_bar_type` include:

None No progress bar.

'tqdm' Use the `tqdm.tqdm()` function to print a progress bar to `sys.stderr`.

'tqdm_notebook' Use the `tqdm.tqdm_notebook()` function to display a progress bar as a Jupyter notebook widget.

'tqdm_gui' Use the `tqdm.tqdm_gui()` function to display a progress bar as a graphical dialog box.

Note that his feature requires version 0.12.0 or later of the `pandas-gbq` package. And it requires the `tqdm` package. Slightly different than `pandas-gbq`, here the default is `None`.

New in version 1.0.0.

Returns

df: DataFrame DataFrame representing results of query.

See also:

pandas_gbq.read_gbq This function in the pandas-gbq library.

DataFrame.to_gbq Write a DataFrame to Google BigQuery.

3.1.15 STATA

read_stata(filepath_or_buffer[, ...])	Read Stata file into DataFrame.

pandas.read_stata

pandas.**read_stata**(*filepath_or_buffer*, *convert_dates=True*, *convert_categoricals=True*, *index_col=None*, *convert_missing=False*, *preserve_dtypes=True*, *columns=None*, *order_categoricals=True*, *chunksize=None*, *iterator=False*, *storage_options=None*)

Read Stata file into DataFrame.

Parameters

filepath_or_buffer [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.dta`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

convert_dates [bool, default True] Convert date variables to DataFrame time values.

convert_categoricals [bool, default True] Read value labels and convert columns to Categorical/Factor variables.

index_col [str, optional] Column to set as index.

convert_missing [bool, default False] Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nan. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissingValue objects.

preserve_dtypes [bool, default True] Preserve Stata datatypes. If False, numeric data are upcast to pandas default types for foreign data (float64 or int64).

columns [list or None] Columns to retain. Columns will be returned in the given order. None returns all columns.

order_categoricals [bool, default True] Flag indicating whether converted categorical data are ordered.

chunksize [int, default None] Return StataReader object for iterations, returns chunks with given number of lines.

iterator [bool, default False] Return StataReader object.

Returns

DataFrame or StataReader

See also:

io.stata.StataReader Low-level reader for Stata data files.

DataFrame.to_stata Export Stata data files.

Notes

Categorical variables read through an iterator may not have the same categories and dtype. This occurs when a variable stored in a DTA file is associated to an incomplete set of value labels that only label a strict subset of the values.

Examples

Read a Stata dta file:

```
>>> df = pd.read_stata('filename.dta')
```

Read a Stata dta file in 10,000 line chunks:

```
>>> itr = pd.read_stata('filename.dta', chunksize=10000)
>>> for chunk in itr:
...     do_something(chunk)
```

StataReader.data_label	Return data label of Stata file.
StataReader.value_labels()	Return a dict, associating each variable name a dict, associating each value its corresponding label.
StataReader.variable_labels()	Return variable labels as a dict, associating each variable name with corresponding label.
StataWriter.write_file()	

pandas.io.stata.StataReader.data_label

property StataReader.**data_label**
Return data label of Stata file.

pandas.io.stata.StataReader.value_labels

StataReader.**value_labels**()
Return a dict, associating each variable name a dict, associating each value its corresponding label.

Returns

dict

pandas.io.stata.StataReader.variable_labels

StataReader.**variable_labels**()
Return variable labels as a dict, associating each variable name with corresponding label.

Returns

dict

pandas.io.stata.StataWriter.write_file

StataWriter.**write_file**()

3.2 General functions

3.2.1 Data manipulations

melt(frame[, id_vars, value_vars, var_name, ...])	Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.
pivot(data[, index, columns, values])	Return reshaped DataFrame organized by given index / column values.
pivot_table(data[, values, index, columns, ...])	Create a spreadsheet-style pivot table as a DataFrame.
crosstab(index, columns[, values, rownames, ...])	Compute a simple cross tabulation of two (or more) factors.
cut(x, bins[, right, labels, retbins, ...])	Bin values into discrete intervals.
qcut(x, q[, labels, retbins, precision, ...])	Quantile-based discretization function.
merge(left, right[, how, on, left_on, ...])	Merge DataFrame or named Series objects with a database-style join.
merge_ordered(left, right[, on, left_on, ...])	Perform merge with optional filling/interpolation.
merge_asof(left, right[, on, left_on, ...])	Perform an asof merge.
concat(objs[, axis, join, ignore_index, ...])	Concatenate pandas objects along a particular axis with optional set logic along the other axes.
get_dummies(data[, prefix, prefix_sep, ...])	Convert categorical variable into dummy/indicator variables.
factorize(values[, sort, na_sentinel, size_hint])	Encode the object as an enumerated type or categorical variable.
unique(values)	Hash table-based unique.
wide_to_long(df, stubnames, i, j[, sep, suffix])	Wide panel to long format.

pandas.melt

pandas.**melt**(*frame*, *id_vars=None*, *value_vars=None*, *var_name=None*, *value_name='value'*, *col_level=None*, *ignore_index=True*)

Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (*id_vars*), while all other columns, considered measured variables (*value_vars*), are "unpivoted" to the row axis, leaving just two non-identifier columns, 'variable' and 'value'.

Parameters

id_vars [tuple, list, or ndarray, optional] Column(s) to use as identifier variables.

value_vars [tuple, list, or ndarray, optional] Column(s) to unpivot. If not specified, uses all columns that are not set as *id_vars*.

var_name [scalar] Name to use for the 'variable' column. If None it uses `frame.columns.name` or 'variable'.

value_name [scalar, default 'value'] Name to use for the 'value' column.

col_level [int or str, optional] If columns are a MultiIndex then use this level to melt.

ignore_index [bool, default True] If True, original index is ignored. If False, the original index is retained. Index labels will be repeated as necessary.

New in version 1.1.0.

Returns

DataFrame Unpivoted DataFrame.

See also:

DataFrame.melt Identical method.

pivot_table Create a spreadsheet-style pivot table as a DataFrame.

DataFrame.pivot Return reshaped DataFrame organized by given index / column values.

DataFrame.explode Explode a DataFrame from list-like columns to long format.

Examples

```
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
...                    'B': {0: 1, 1: 3, 2: 5},
...                    'C': {0: 2, 1: 4, 2: 6}})
>>> df
   A  B  C
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
```

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B', 'C'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
3  a        C      2
4  b        C      4
5  c        C      6
```

The names of 'variable' and 'value' columns can be customized:

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B'],
...         var_name='myVarname', value_name='myValname')
   A myVarname  myValname
0  a         B          1
1  b         B          3
2  c         B          5
```

Original index values can be kept around:

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B', 'C'], ignore_index=False)
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
0  a        C      2
1  b        C      4
2  c        C      6
```

If you have multi-index columns:

```
>>> df.columns = [list('ABC'), list('DEF')]
>>> df
   A  B  C
   D  E  F
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> pd.melt(df, col_level=0, id_vars=['A'], value_vars=['B'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
```

```
>>> pd.melt(df, id_vars=[('A', 'D')], value_vars=[('B', 'E')])
  (A, D) variable_0 variable_1  value
0      a          B          E      1
1      b          B          E      3
2      c          B          E      5
```

pandas.pivot

pandas.**pivot**(*data*, *index=None*, *columns=None*, *values=None*)

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a "pivot" table) based on column values. Uses unique values from specified *index* / *columns* to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the *User Guide* for more on reshaping.

Parameters

data [DataFrame]

index [str or object or a list of str, optional] Column to use to make new frame's index. If None, uses existing index.

Changed in version 1.1.0: Also accept list of index names.

columns [str or object or a list of str] Column to use to make new frame's columns.

Changed in version 1.1.0: Also accept list of columns names.

values [str, object or a list of the previous, optional] Column(s) to use for populating new frame's values. If not specified, all remaining columns will be used and the result will have hierarchically indexed columns.

Returns

DataFrame Returns reshaped DataFrame.

Raises

ValueError: When there are any *index*, *columns* combinations with multiple values. *DataFrame.pivot_table* when you need to aggregate.

See also:

DataFrame.pivot_table Generalization of pivot that can handle duplicate values for one index/column pair.

DataFrame.unstack Pivot based on the index values instead of a column.

wide_to_long Wide panel to long format. Less flexible but more user-friendly than melt.

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods.

Examples

```
>>> df = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two',
...                            'two'],
...                    'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
...                    'baz': [1, 2, 3, 4, 5, 6],
...                    'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
>>> df
    foo   bar  baz  zoo
0   one   A    1    x
1   one   B    2    y
2   one   C    3    z
3   two   A    4    q
4   two   B    5    w
5   two   C    6    t
```

```
>>> df.pivot(index='foo', columns='bar', values='baz')
bar  A   B   C
foo
one  1   2   3
two  4   5   6
```

```
>>> df.pivot(index='foo', columns='bar')['baz']
bar  A   B   C
foo
one  1   2   3
two  4   5   6
```

```
>>> df.pivot(index='foo', columns='bar', values=['baz', 'zoo'])
      baz       zoo
bar   A  B  C   A  B  C
foo
one   1  2  3   x  y  z
two   4  5  6   q  w  t
```

You could also assign a list of column names or a list of index names.

```
>>> df = pd.DataFrame({
...         "lev1": [1, 1, 1, 2, 2, 2],
...         "lev2": [1, 1, 2, 1, 1, 2],
...         "lev3": [1, 2, 1, 2, 1, 2],
...         "lev4": [1, 2, 3, 4, 5, 6],
...         "values": [0, 1, 2, 3, 4, 5]})
>>> df
    lev1 lev2 lev3 lev4 values
0   1    1    1    1    0
1   1    1    2    2    1
2   1    2    1    3    2
3   2    1    2    4    3
4   2    1    1    5    4
5   2    2    2    6    5
```

```
>>> df.pivot(index="lev1", columns=["lev2", "lev3"],values="values")
lev2    1          2
lev3    1    2     1    2
lev1
1     0.0  1.0   2.0  NaN
2     4.0  3.0   NaN  5.0
```

```
>>> df.pivot(index=["lev1", "lev2"], columns=["lev3"],values="values")
      lev3    1    2
lev1  lev2
   1     1  0.0  1.0
         2  2.0  NaN
   2     1  4.0  3.0
         2  NaN  5.0
```

A ValueError is raised if there are any duplicates.

```
>>> df = pd.DataFrame({"foo": ['one', 'one', 'two', 'two'],
...                    "bar": ['A', 'A', 'B', 'C'],
...                    "baz": [1, 2, 3, 4]})
>>> df
   foo bar  baz
0  one   A    1
1  one   A    2
2  two   B    3
3  two   C    4
```

Notice that the first two rows are the same for our *index* and *columns* arguments.

```
>>> df.pivot(index='foo', columns='bar', values='baz')
Traceback (most recent call last):
   ...
ValueError: Index contains duplicate entries, cannot reshape
```

pandas.pivot_table

pandas.**pivot_table**(*data*, *values=None*, *index=None*, *columns=None*, *aggfunc='mean'*, *fill_value=None*, *margins=False*, *dropna=True*, *margins_name='All'*, *observed=False*)

Create a spreadsheet-style pivot table as a DataFrame.

The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame.

Parameters

data [DataFrame]

values [column to aggregate, optional]

index [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc [function, list of functions, dict, default numpy.mean] If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions.

fill_value [scalar, default None] Value to replace missing values with (in the resulting pivot table, after aggregation).

margins [bool, default False] Add all row / columns (e.g. for subtotal / grand totals).

dropna [bool, default True] Do not include columns whose entries are all NaN.

margins_name [str, default 'All'] Name of the row / column that will contain the totals when margins is True.

observed [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

Changed in version 0.25.0.

Returns

DataFrame An Excel style pivot table.

See also:

DataFrame.pivot Pivot without aggregation that can handle non-numeric data.

DataFrame.melt Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

wide_to_long Wide panel to long format. Less flexible but more user-friendly than melt.

Examples

```
>>> df = pd.DataFrame({"A": ["foo", "foo", "foo", "foo", "foo",
...                          "bar", "bar", "bar", "bar"],
...                    "B": ["one", "one", "one", "two", "two",
...                          "one", "one", "two", "two"],
...                    "C": ["small", "large", "large", "small",
...                          "small", "large", "small", "small",
...                          "large"],
...                    "D": [1, 2, 2, 3, 3, 4, 5, 6, 7],
...                    "E": [2, 4, 5, 5, 6, 6, 8, 9, 9]})
>>> df
     A    B      C  D  E
0  foo  one  small  1  2
1  foo  one  large  2  4
2  foo  one  large  2  5
3  foo  two  small  3  5
4  foo  two  small  3  6
5  bar  one  large  4  6
6  bar  one  small  5  8
7  bar  two  small  6  9
8  bar  two  large  7  9
```

This first example aggregates values by taking the sum.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                        columns=['C'], aggfunc=np.sum)
>>> table
C        large  small
A   B
bar one    4.0    5.0
    two    7.0    6.0
foo one    4.0    1.0
    two    NaN    6.0
```

We can also fill missing values using the *fill_value* parameter.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                        columns=['C'], aggfunc=np.sum, fill_value=0)
>>> table
C        large  small
A   B
bar one      4      5
    two      7      6
foo one      4      1
    two      0      6
```

The next example aggregates by taking the mean across multiple columns.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                        aggfunc={'D': np.mean,
...                                 'E': np.mean})
>>> table
                D         E
A   C
bar large  5.500000  7.500000
    small  5.500000  8.500000
```

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```
foo large  2.000000  4.500000
    small  2.333333  4.333333
```

We can also calculate multiple types of aggregations for any given value column.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                        aggfunc={'D': np.mean,
...                                 'E': [min, max, np.mean]})
>>> table
                D    E
             mean  max      mean  min
A   C
bar large  5.500000  9.0  7.500000  6.0
    small  5.500000  9.0  8.500000  8.0
foo large  2.000000  5.0  4.500000  4.0
    small  2.333333  6.0  4.333333  2.0
```

pandas.crosstab

pandas.**crosstab**(*index*, *columns*, *values=None*, *rownames=None*, *colnames=None*, *aggfunc=None*, *margins=False*, *margins_name='All'*, *dropna=True*, *normalize=False*)

Compute a simple cross tabulation of two (or more) factors. By default computes a frequency table of the factors unless an array of values and an aggregation function are passed.

Parameters

index [array-like, Series, or list of arrays/Series] Values to group by in the rows.

columns [array-like, Series, or list of arrays/Series] Values to group by in the columns.

values [array-like, optional] Array of values to aggregate according to the factors. Requires *aggfunc* be specified.

rownames [sequence, default None] If passed, must match number of row arrays passed.

colnames [sequence, default None] If passed, must match number of column arrays passed.

aggfunc [function, optional] If specified, requires *values* be specified as well.

margins [bool, default False] Add row/column margins (subtotals).

margins_name [str, default 'All'] Name of the row/column that will contain the totals when margins is True.

dropna [bool, default True] Do not include columns whose entries are all NaN.

normalize [bool, {'all', 'index', 'columns'}, or {0,1}, default False] Normalize by dividing all values by the sum of values.

- If passed 'all' or *True*, will normalize over all values.
- If passed 'index' will normalize over each row.
- If passed 'columns' will normalize over each column.
- If margins is *True*, will also normalize margin values.

Returns

DataFrame Cross tabulation of the data.

See also:

DataFrame.pivot Reshape data based on column values.

pivot_table Create a pivot table as a DataFrame.

Notes

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified.

Any input passed containing Categorical data will have **all** of its categories included in the cross-tabulation, even if the actual data does not contain any instances of a particular category.

In the event that there aren't overlapping indexes an empty DataFrame will be returned.

Examples

```
>>> a = np.array(["foo", "foo", "foo", "foo", "bar", "bar",
...               "bar", "bar", "foo", "foo", "foo"], dtype=object)
>>> b = np.array(["one", "one", "one", "two", "one", "one",
...               "one", "two", "two", "two", "one"], dtype=object)
>>> c = np.array(["dull", "dull", "shiny", "dull", "dull", "shiny",
...               "shiny", "dull", "shiny", "shiny", "shiny"],
...              dtype=object)
>>> pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
b   one        two
c   dull shiny dull shiny
a
bar    1     2    1     0
foo    2     2    1     2
```

Here 'c' and 'f' are not represented in the data and will not be shown in the output because dropna is True by default. Set dropna=False to preserve categories with no data.

```
>>> foo = pd.Categorical(['a', 'b'], categories=['a', 'b', 'c'])
>>> bar = pd.Categorical(['d', 'e'], categories=['d', 'e', 'f'])
>>> pd.crosstab(foo, bar)
col_0  d  e
row_0
a      1  0
b      0  1
>>> pd.crosstab(foo, bar, dropna=False)
col_0  d  e  f
row_0
a      1  0  0
b      0  1  0
c      0  0  0
```

pandas.cut

pandas.**cut**(*x*, *bins*, *right=True*, *labels=None*, *retbins=False*, *precision=3*, *include_lowest=False*, *duplicates='raise'*, *ordered=True*)

Bin values into discrete intervals.

Use *cut* when you need to segment and sort data values into bins. This function is also useful for going from a continuous variable to a categorical variable. For example, *cut* could convert ages to groups of age ranges. Supports binning into an equal number of bins, or a pre-specified array of bins.

Parameters

x [array-like] The input array to be binned. Must be 1-dimensional.

bins [int, sequence of scalars, or IntervalIndex] The criteria to bin by.

- int : Defines the number of equal-width bins in the range of *x*. The range of *x* is extended by .1% on each side to include the minimum and maximum values of *x*.
- sequence of scalars : Defines the bin edges allowing for non-uniform width. No extension of the range of *x* is done.
- IntervalIndex : Defines the exact bins to be used. Note that IntervalIndex for *bins* must be non-overlapping.

right [bool, default True] Indicates whether *bins* includes the rightmost edge or not. If `right == True` (the default), then the *bins* `[1, 2, 3, 4]` indicate (1,2], (2,3], (3,4]. This argument is ignored when *bins* is an IntervalIndex.

labels [array or False, default None] Specifies the labels for the returned bins. Must be the same length as the resulting bins. If False, returns only integer indicators of the bins. This affects the type of the output container (see below). This argument is ignored when *bins* is an IntervalIndex. If True, raises an error. When *ordered=False*, labels must be provided.

retbins [bool, default False] Whether to return the bins or not. Useful when bins is provided as a scalar.

precision [int, default 3] The precision at which to store and display the bins labels.

include_lowest [bool, default False] Whether the first interval should be left-inclusive or not.

duplicates [{default 'raise', 'drop'}, optional] If bin edges are not unique, raise ValueError or drop non-uniques.

ordered [bool, default True] Whether the labels are ordered or not. Applies to returned types Categorical and Series (with Categorical dtype). If True, the resulting categorical will be ordered. If False, the resulting categorical will be unordered (labels must be provided).

New in version 1.1.0.

Returns

out [Categorical, Series, or ndarray] An array-like object representing the respective bin for each value of *x*. The type depends on the value of *labels*.

- True (default) : returns a Series for Series *x* or a Categorical for all other inputs. The values stored within are Interval dtype.
- sequence of scalars : returns a Series for Series *x* or a Categorical for all other inputs. The values stored within are whatever the type in the sequence is.
- False : returns an ndarray of integers.

bins [numpy.ndarray or IntervalIndex.] The computed or specified bins. Only returned when *retbins=True*. For scalar or sequence *bins*, this is an ndarray with the computed bins. If set *duplicates=drop*, *bins* will drop non-unique bin. For an IntervalIndex *bins*, this is equal to *bins*.

See also:

qcut Discretize variable into equal-sized buckets based on rank or based on sample quantiles.

Categorical Array type for storing data that come from a fixed set of values.

Series One-dimensional array with axis labels (including time series).

IntervalIndex Immutable Index implementing an ordered, sliceable set.

Notes

Any NA values will be NA in the result. Out of bounds values will be NA in the resulting Series or Categorical object.

Examples

Discretize into three equal-sized bins.

```
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3)
...
[(0.994, 3.0], (5.0, 7.0], (3.0, 5.0], (3.0, 5.0], (5.0, 7.0], ...
Categories (3, interval[float64]): [(0.994, 3.0] < (3.0, 5.0] ...
```

```
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3, retbins=True)
...
([(0.994, 3.0], (5.0, 7.0], (3.0, 5.0], (3.0, 5.0], (5.0, 7.0], ...
Categories (3, interval[float64]): [(0.994, 3.0] < (3.0, 5.0] ...
array([0.994, 3.   , 5.   , 7.   ]))
```

Discovers the same bins, but assign them specific labels. Notice that the returned Categorical's categories are *labels* and is ordered.

```
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]),
...        3, labels=["bad", "medium", "good"])
['bad', 'good', 'medium', 'medium', 'good', 'bad']
Categories (3, object): ['bad' < 'medium' < 'good']
```

`ordered=False` will result in unordered categories when labels are passed. This parameter can be used to allow non-unique labels:

```
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3,
...        labels=["B", "A", "B"], ordered=False)
['B', 'B', 'A', 'A', 'B', 'B']
Categories (2, object): ['A', 'B']
```

`labels=False` implies you just want the bins back.

```
>>> pd.cut([0, 1, 1, 2], bins=4, labels=False)
array([0, 1, 1, 3])
```

Passing a Series as an input returns a Series with categorical dtype:

```
>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
...               index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, 3)
...
a    (1.992, 4.667]
b    (1.992, 4.667]
c    (4.667, 7.333]
d     (7.333, 10.0]
e     (7.333, 10.0]
dtype: category
Categories (3, interval[float64]): [(1.992, 4.667] < (4.667, ...
```

Passing a Series as an input returns a Series with mapping value. It is used to map numerically to intervals based on bins.

```
>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
...               index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, [0, 2, 4, 6, 8, 10], labels=False, retbins=True, right=False)
...
(a    1.0
 b    2.0
 c    3.0
 d    4.0
 e    NaN
 dtype: float64,
 array([ 0,  2,  4,  6,  8, 10]))
```

Use *drop* optional when bins is not unique

```
>>> pd.cut(s, [0, 2, 4, 6, 10, 10], labels=False, retbins=True,
...        right=False, duplicates='drop')
...
(a    1.0
 b    2.0
 c    3.0
 d    3.0
 e    NaN
 dtype: float64,
 array([ 0,  2,  4,  6, 10]))
```

Passing an IntervalIndex for *bins* results in those categories exactly. Notice that values not covered by the IntervalIndex are set to NaN. 0 is to the left of the first bin (which is closed on the right), and 1.5 falls between two bins.

```
>>> bins = pd.IntervalIndex.from_tuples([(0, 1), (2, 3), (4, 5)])
>>> pd.cut([0, 0.5, 1.5, 2.5, 4.5], bins)
[NaN, (0.0, 1.0], NaN, (2.0, 3.0], (4.0, 5.0]]
Categories (3, interval[int64]): [(0, 1] < (2, 3] < (4, 5]]
```

pandas.qcut

pandas.**qcut**(*x*, *q*, *labels=None*, *retbins=False*, *precision=3*, *duplicates='raise'*)

Quantile-based discretization function.

Discretize variable into equal-sized buckets based on rank or based on sample quantiles. For example 1000 values for 10 quantiles would produce a Categorical object indicating quantile membership for each data point.

Parameters

x [1d ndarray or Series]

q [int or list-like of float] Number of quantiles. 10 for deciles, 4 for quartiles, etc. Alternately array of quantiles, e.g. [0, .25, .5, .75, 1.] for quartiles.

labels [array or False, default None] Used as labels for the resulting bins. Must be of the same length as the resulting bins. If False, return only integer indicators of the bins. If True, raises an error.

retbins [bool, optional] Whether to return the (bins, labels) or not. Can be useful if bins is given as a scalar.

precision [int, optional] The precision at which to store and display the bins labels.

duplicates [{default 'raise', 'drop'}, optional] If bin edges are not unique, raise ValueError or drop non-uniques.

Returns

out [Categorical or Series or array of integers if labels is False] The return type (Categorical or Series) depends on the input: a Series of type category if input is a Series else Categorical. Bins are represented as categories when categorical data is returned.

bins [ndarray of floats] Returned only if *retbins* is True.

Notes

Out of bounds values will be NA in the resulting Categorical object

Examples

```
>>> pd.qcut(range(5), 4)
...
[(-0.001, 1.0], (-0.001, 1.0], (1.0, 2.0], (2.0, 3.0], (3.0, 4.0]]
Categories (4, interval[float64]): [(-0.001, 1.0] < (1.0, 2.0] ...
```

```
>>> pd.qcut(range(5), 3, labels=["good", "medium", "bad"])
...
[good, good, medium, bad, bad]
Categories (3, object): [good < medium < bad]
```

```
>>> pd.qcut(range(5), 4, labels=False)
array([0, 0, 1, 2, 3])
```

pandas.merge

pandas.**merge**(*left*, *right*, *how='inner'*, *on=None*, *left_on=None*, *right_on=None*, *left_index=False*, *right_index=False*, *sort=False*, *suffixes=('_x', '_y')*, *copy=True*, *indicator=False*, *validate=None*)

Merge DataFrame or named Series objects with a database-style join.

The join is done on columns or indexes. If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on. When performing a cross merge, no column specifications to merge on are allowed.

Parameters

left [DataFrame]

right [DataFrame or named Series] Object to merge with.

how [{'left', 'right', 'outer', 'inner', 'cross'}, default 'inner'] Type of merge to be performed.

- left: use only keys from left frame, similar to a SQL left outer join; preserve key order.
- right: use only keys from right frame, similar to a SQL right outer join; preserve key order.
- outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.
- inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.
- cross: creates the cartesian product from both frames, preserves the order of the left keys.

  New in version 1.2.0.

on [label or list] Column or index level names to join on. These must be found in both DataFrames. If *on* is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.

left_on [label or list, or array-like] Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.

right_on [label or list, or array-like] Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.

left_index [bool, default False] Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels.

right_index [bool, default False] Use the index from the right DataFrame as the join key. Same caveats as left_index.

sort [bool, default False] Sort the join keys lexicographically in the result DataFrame. If False, the order of the join keys depends on the join type (how keyword).

suffixes [list-like, default is ("_x", "_y")] A length-2 sequence where each element is optionally a string indicating the suffix to add to overlapping column names in *left* and *right* respectively. Pass a value of *None* instead of a string to indicate that the column name from *left* or *right* should be left as-is, with no suffix. At least one of the values must not be None.

copy [bool, default True] If False, avoid copy if possible.

indicator [bool or str, default False] If True, adds a column to the output DataFrame called "_merge" with information on the source of each row. The column can be given a different name by providing a string argument. The column will have a Categorical type with the value of "left_only" for observations whose merge key only appears in the left DataFrame, "right_only" for observations whose merge key only appears in the right DataFrame, and "both" if the observation's merge key is found in both DataFrames.

validate [str, optional] If specified, checks if merge is of specified type.

- "one_to_one" or "1:1": check if merge keys are unique in both left and right datasets.
- "one_to_many" or "1:m": check if merge keys are unique in left dataset.
- "many_to_one" or "m:1": check if merge keys are unique in right dataset.
- "many_to_many" or "m:m": allowed, but does not result in checks.

Returns

DataFrame A DataFrame of the two merged objects.

See also:

merge_ordered Merge with optional filling/interpolation.

merge_asof Merge on nearest keys.

DataFrame.join Similar method using indices.

Notes

Support for specifying index levels as the *on*, *left_on*, and *right_on* parameters was added in version 0.23.0 Support for merging named Series objects was added in version 0.24.0

Examples

```
>>> df1 = pd.DataFrame({'lkey': ['foo', 'bar', 'baz', 'foo'],
...                     'value': [1, 2, 3, 5]})
>>> df2 = pd.DataFrame({'rkey': ['foo', 'bar', 'baz', 'foo'],
...                     'value': [5, 6, 7, 8]})
>>> df1
    lkey value
0   foo      1
1   bar      2
2   baz      3
3   foo      5
>>> df2
    rkey value
0   foo      5
1   bar      6
2   baz      7
3   foo      8
```

Merge df1 and df2 on the lkey and rkey columns. The value columns have the default suffixes, _x and _y, appended.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey')
  lkey  value_x rkey  value_y
0  foo        1  foo        5
1  foo        1  foo        8
2  foo        5  foo        5
3  foo        5  foo        8
4  bar        2  bar        6
5  baz        3  baz        7
```

Merge DataFrames df1 and df2 with specified left and right suffixes appended to any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey',
...           suffixes=('_left', '_right'))
  lkey  value_left rkey  value_right
0  foo           1  foo            5
1  foo           1  foo            8
2  foo           5  foo            5
3  foo           5  foo            8
4  bar           2  bar            6
5  baz           3  baz            7
```

Merge DataFrames df1 and df2, but raise an exception if the DataFrames have any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey', suffixes=(False, False))
Traceback (most recent call last):
...
ValueError: columns overlap but no suffix specified:
    Index(['value'], dtype='object')
```

```
>>> df1 = pd.DataFrame({'a': ['foo', 'bar'], 'b': [1, 2]})
>>> df2 = pd.DataFrame({'a': ['foo', 'baz'], 'c': [3, 4]})
>>> df1
      a  b
0   foo  1
1   bar  2
>>> df2
      a  c
0   foo  3
1   baz  4
```

```
>>> df1.merge(df2, how='inner', on='a')
      a  b  c
0   foo  1  3
```

```
>>> df1.merge(df2, how='left', on='a')
      a  b  c
0   foo  1  3.0
1   bar  2  NaN
```

```
>>> df1 = pd.DataFrame({'left': ['foo', 'bar']})
>>> df2 = pd.DataFrame({'right': [7, 8]})
>>> df1
    left
0   foo
1   bar
>>> df2
```

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```
    right
0   7
1   8
```

```
>>> df1.merge(df2, how='cross')
   left  right
0   foo      7
1   foo      8
2   bar      7
3   bar      8
```

pandas.merge_ordered

pandas.**merge_ordered**(*left*, *right*, *on=None*, *left_on=None*, *right_on=None*, *left_by=None*, *right_by=None*, *fill_method=None*, *suffixes=('_x', '_y')*, *how='outer'*)

Perform merge with optional filling/interpolation.

Designed for ordered data like time series data. Optionally perform group-wise merge (see examples).

Parameters

left [DataFrame]

right [DataFrame]

on [label or list] Field names to join on. Must be found in both DataFrames.

left_on [label or list, or array-like] Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns.

right_on [label or list, or array-like] Field names to join on in right DataFrame or vector/list of vectors per left_on docs.

left_by [column name or list of column names] Group left DataFrame by group columns and merge piece by piece with right DataFrame.

right_by [column name or list of column names] Group right DataFrame by group columns and merge piece by piece with left DataFrame.

fill_method [{'ffill', None}, default None] Interpolation method for data.

suffixes [list-like, default is ("_x", "_y")] A length-2 sequence where each element is optionally a string indicating the suffix to add to overlapping column names in *left* and *right* respectively. Pass a value of *None* instead of a string to indicate that the column name from *left* or *right* should be left as-is, with no suffix. At least one of the values must not be None.

Changed in version 0.25.0.

how [{'left', 'right', 'outer', 'inner'}, default 'outer']

- left: use only keys from left frame (SQL: left outer join)
- right: use only keys from right frame (SQL: right outer join)
- outer: use union of keys from both frames (SQL: full outer join)
- inner: use intersection of keys from both frames (SQL: inner join).

Returns

DataFrame The merged DataFrame output type will the be same as 'left', if it is a subclass of DataFrame.

See also:

merge Merge with a database-style join.

merge_asof Merge on nearest keys.

Examples

```
>>> df1 = pd.DataFrame(
...     {
...         "key": ["a", "c", "e", "a", "c", "e"],
...         "lvalue": [1, 2, 3, 1, 2, 3],
...         "group": ["a", "a", "a", "b", "b", "b"]
...     }
... )
>>> df1
  key  lvalue group
0   a       1     a
1   c       2     a
2   e       3     a
3   a       1     b
4   c       2     b
5   e       3     b
```

```
>>> df2 = pd.DataFrame({"key": ["b", "c", "d"], "rvalue": [1, 2, 3]})
>>> df2
  key  rvalue
0   b       1
1   c       2
2   d       3
```

```
>>> merge_ordered(df1, df2, fill_method="ffill", left_by="group")
  key  lvalue group  rvalue
0   a       1     a     NaN
1   b       1     a     1.0
2   c       2     a     2.0
3   d       2     a     3.0
4   e       3     a     3.0
5   a       1     b     NaN
6   b       1     b     1.0
7   c       2     b     2.0
8   d       2     b     3.0
9   e       3     b     3.0
```

pandas.merge_asof

pandas.**merge_asof**(*left*, *right*, *on=None*, *left_on=None*, *right_on=None*, *left_index=False*, *right_index=False*, *by=None*, *left_by=None*, *right_by=None*, *suffixes=('_x', '_y')*, *tolerance=None*, *allow_exact_matches=True*, *direction='backward'*)

Perform an asof merge.

This is similar to a left-join except that we match on nearest key rather than equal keys. Both DataFrames must be sorted by the key.

For each row in the left DataFrame:

- A "backward" search selects the last row in the right DataFrame whose 'on' key is less than or equal to the left's key.
- A "forward" search selects the first row in the right DataFrame whose 'on' key is greater than or equal to the left's key.
- A "nearest" search selects the row in the right DataFrame whose 'on' key is closest in absolute distance to the left's key.

The default is "backward" and is compatible in versions below 0.20.0. The direction parameter was added in version 0.20.0 and introduces "forward" and "nearest".

Optionally match on equivalent keys with 'by' before searching with 'on'.

Parameters

left [DataFrame]

right [DataFrame]

on [label] Field name to join on. Must be found in both DataFrames. The data MUST be ordered. Furthermore this must be a numeric column, such as datetimelike, integer, or float. On or left_on/right_on must be given.

left_on [label] Field name to join on in left DataFrame.

right_on [label] Field name to join on in right DataFrame.

left_index [bool] Use the index of the left DataFrame as the join key.

right_index [bool] Use the index of the right DataFrame as the join key.

by [column name or list of column names] Match on these columns before performing merge operation.

left_by [column name] Field names to match on in the left DataFrame.

right_by [column name] Field names to match on in the right DataFrame.

suffixes [2-length sequence (tuple, list, ...)] Suffix to apply to overlapping column names in the left and right side, respectively.

tolerance [int or Timedelta, optional, default None] Select asof tolerance within this range; must be compatible with the merge index.

allow_exact_matches [bool, default True]

- If True, allow matching with the same 'on' value (i.e. less-than-or-equal-to / greater-than-or-equal-to)
- If False, don't match the same 'on' value (i.e., strictly less-than / strictly greater-than).

direction ['backward' (default), 'forward', or 'nearest'] Whether to search for prior, subsequent, or closest matches.

Returns

merged [DataFrame]

See also:

merge Merge with a database-style join.

merge_ordered Merge with optional filling/interpolation.

Examples

```
>>> left = pd.DataFrame({"a": [1, 5, 10], "left_val": ["a", "b", "c"]})
>>> left
    a left_val
0   1        a
1   5        b
2  10        c
```

```
>>> right = pd.DataFrame({"a": [1, 2, 3, 6, 7], "right_val": [1, 2, 3, 6, 7]})
>>> right
   a  right_val
0  1          1
1  2          2
2  3          3
3  6          6
4  7          7
```

```
>>> pd.merge_asof(left, right, on="a")
    a left_val  right_val
0   1        a          1
1   5        b          3
2  10        c          7
```

```
>>> pd.merge_asof(left, right, on="a", allow_exact_matches=False)
    a left_val  right_val
0   1        a        NaN
1   5        b        3.0
2  10        c        7.0
```

```
>>> pd.merge_asof(left, right, on="a", direction="forward")
    a left_val  right_val
0   1        a        1.0
1   5        b        6.0
2  10        c        NaN
```

```
>>> pd.merge_asof(left, right, on="a", direction="nearest")
    a left_val  right_val
0   1        a          1
1   5        b          6
2  10        c          7
```

We can use indexed DataFrames as well.

```
>>> left = pd.DataFrame({"left_val": ["a", "b", "c"]}, index=[1, 5, 10])
>>> left
   left_val
1         a
5         b
10        c
```

```
>>> right = pd.DataFrame({"right_val": [1, 2, 3, 6, 7]}, index=[1, 2, 3, 6, 7])
>>> right
   right_val
1          1
2          2
3          3
6          6
7          7
```

```
>>> pd.merge_asof(left, right, left_index=True, right_index=True)
   left_val  right_val
1         a          1
5         b          3
10        c          7
```

Here is a real-world times-series example

```
>>> quotes = pd.DataFrame(
...     {
...         "time": [
...             pd.Timestamp("2016-05-25 13:30:00.023"),
...             pd.Timestamp("2016-05-25 13:30:00.023"),
...             pd.Timestamp("2016-05-25 13:30:00.030"),
...             pd.Timestamp("2016-05-25 13:30:00.041"),
...             pd.Timestamp("2016-05-25 13:30:00.048"),
...             pd.Timestamp("2016-05-25 13:30:00.049"),
...             pd.Timestamp("2016-05-25 13:30:00.072"),
...             pd.Timestamp("2016-05-25 13:30:00.075")
...         ],
...         "ticker": [
...                 "GOOG",
...                 "MSFT",
...                 "MSFT",
...                 "MSFT",
...                 "GOOG",
...                 "AAPL",
...                 "GOOG",
...                 "MSFT"
...             ],
...             "bid": [720.50, 51.95, 51.97, 51.99, 720.50, 97.99, 720.50, 52.01],
...             "ask": [720.93, 51.96, 51.98, 52.00, 720.93, 98.01, 720.88, 52.03]
...     }
... )
>>> quotes
                     time ticker     bid     ask
0 2016-05-25 13:30:00.023   GOOG  720.50  720.93
1 2016-05-25 13:30:00.023   MSFT   51.95   51.96
2 2016-05-25 13:30:00.030   MSFT   51.97   51.98
3 2016-05-25 13:30:00.041   MSFT   51.99   52.00
4 2016-05-25 13:30:00.048   GOOG  720.50  720.93
```

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```
5 2016-05-25 13:30:00.049   AAPL   97.99   98.01
6 2016-05-25 13:30:00.072   GOOG  720.50  720.88
7 2016-05-25 13:30:00.075   MSFT   52.01   52.03
```

```
>>> trades = pd.DataFrame(
...         {
...             "time": [
...                 pd.Timestamp("2016-05-25 13:30:00.023"),
...                 pd.Timestamp("2016-05-25 13:30:00.038"),
...                 pd.Timestamp("2016-05-25 13:30:00.048"),
...                 pd.Timestamp("2016-05-25 13:30:00.048"),
...                 pd.Timestamp("2016-05-25 13:30:00.048")
...             ],
...             "ticker": ["MSFT", "MSFT", "GOOG", "GOOG", "AAPL"],
...             "price": [51.95, 51.95, 720.77, 720.92, 98.0],
...             "quantity": [75, 155, 100, 100, 100]
...         }
...     )
>>> trades
                     time ticker   price  quantity
0 2016-05-25 13:30:00.023   MSFT   51.95        75
1 2016-05-25 13:30:00.038   MSFT   51.95       155
2 2016-05-25 13:30:00.048   GOOG  720.77       100
3 2016-05-25 13:30:00.048   GOOG  720.92       100
4 2016-05-25 13:30:00.048   AAPL   98.00       100
```

By default we are taking the asof of the quotes

```
>>> pd.merge_asof(trades, quotes, on="time", by="ticker")
                     time ticker   price  quantity     bid     ask
0 2016-05-25 13:30:00.023   MSFT   51.95        75   51.95   51.96
1 2016-05-25 13:30:00.038   MSFT   51.95       155   51.97   51.98
2 2016-05-25 13:30:00.048   GOOG  720.77       100  720.50  720.93
3 2016-05-25 13:30:00.048   GOOG  720.92       100  720.50  720.93
4 2016-05-25 13:30:00.048   AAPL   98.00       100     NaN     NaN
```

We only asof within 2ms between the quote time and the trade time

```
>>> pd.merge_asof(
...     trades, quotes, on="time", by="ticker", tolerance=pd.Timedelta("2ms")
... )
                     time ticker   price  quantity     bid     ask
0 2016-05-25 13:30:00.023   MSFT   51.95        75   51.95   51.96
1 2016-05-25 13:30:00.038   MSFT   51.95       155     NaN     NaN
2 2016-05-25 13:30:00.048   GOOG  720.77       100  720.50  720.93
3 2016-05-25 13:30:00.048   GOOG  720.92       100  720.50  720.93
4 2016-05-25 13:30:00.048   AAPL   98.00       100     NaN     NaN
```

We only asof within 10ms between the quote time and the trade time and we exclude exact matches on time. However *prior* data will propagate forward

```
>>> pd.merge_asof(
...     trades,
...     quotes,
...     on="time",
...     by="ticker",
```

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```
...     tolerance=pd.Timedelta("10ms"),
...     allow_exact_matches=False
... )
                     time ticker   price  quantity     bid     ask
0 2016-05-25 13:30:00.023   MSFT   51.95        75     NaN     NaN
1 2016-05-25 13:30:00.038   MSFT   51.95       155   51.97   51.98
2 2016-05-25 13:30:00.048   GOOG  720.77       100     NaN     NaN
3 2016-05-25 13:30:00.048   GOOG  720.92       100     NaN     NaN
4 2016-05-25 13:30:00.048   AAPL   98.00       100     NaN     NaN
```

pandas.concat

pandas.**concat**(*objs*, *axis=0*, *join='outer'*, *ignore_index=False*, *keys=None*, *levels=None*, *names=None*, *verify_integrity=False*, *sort=False*, *copy=True*)

Concatenate pandas objects along a particular axis with optional set logic along the other axes.

Can also add a layer of hierarchical indexing on the concatenation axis, which may be useful if the labels are the same (or overlapping) on the passed axis number.

Parameters

objs [a sequence or mapping of Series or DataFrame objects] If a mapping is passed, the sorted keys will be used as the *keys* argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a ValueError will be raised.

axis [{0/'index', 1/'columns'}, default 0] The axis to concatenate along.

join [{'inner', 'outer'}, default 'outer'] How to handle indexes on other axis (or axes).

ignore_index [bool, default False] If True, do not use the index values along the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.

keys [sequence, default None] If multiple levels passed, should contain tuples. Construct hierarchical index using the passed keys as the outermost level.

levels [list of sequences, default None] Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.

names [list, default None] Names for the levels in the resulting hierarchical index.

verify_integrity [bool, default False] Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.

sort [bool, default False] Sort non-concatenation axis if it is not already aligned when *join* is 'outer'. This has no effect when `join='inner'`, which already preserves the order of the non-concatenation axis.

Changed in version 1.0.0: Changed to not sort by default.

copy [bool, default True] If False, do not copy data unnecessarily.

Returns

object, type of objs When concatenating all `Series` along the index (axis=0), a `Series` is returned. When `objs` contains at least one `DataFrame`, a `DataFrame` is returned. When concatenating along the columns (axis=1), a `DataFrame` is returned.

See also:

Series.append Concatenate Series.

DataFrame.append Concatenate DataFrames.

DataFrame.join Join DataFrames using indexes.

DataFrame.merge Merge DataFrames by indexes or columns.

Notes

The keys, levels, and names arguments are all optional.

A walkthrough of how this method fits in with other tools for combining pandas objects can be found here.

Examples

Combine two `Series`.

```
>>> s1 = pd.Series(['a', 'b'])
>>> s2 = pd.Series(['c', 'd'])
>>> pd.concat([s1, s2])
0    a
1    b
0    c
1    d
dtype: object
```

Clear the existing index and reset it in the result by setting the `ignore_index` option to `True`.

```
>>> pd.concat([s1, s2], ignore_index=True)
0    a
1    b
2    c
3    d
dtype: object
```

Add a hierarchical index at the outermost level of the data with the `keys` option.

```
>>> pd.concat([s1, s2], keys=['s1', 's2'])
s1  0    a
    1    b
s2  0    c
    1    d
dtype: object
```

Label the index keys you create with the `names` option.

```
>>> pd.concat([s1, s2], keys=['s1', 's2'],
...           names=['Series name', 'Row ID'])
Series name  Row ID
s1           0         a
             1         b
s2           0         c
             1         d
dtype: object
```

Combine two `DataFrame` objects with identical columns.

```
>>> df1 = pd.DataFrame([['a', 1], ['b', 2]],
...                    columns=['letter', 'number'])
>>> df1
  letter  number
0      a       1
1      b       2
>>> df2 = pd.DataFrame([['c', 3], ['d', 4]],
...                    columns=['letter', 'number'])
>>> df2
  letter  number
0      c       3
1      d       4
>>> pd.concat([df1, df2])
  letter  number
0      a       1
1      b       2
0      c       3
1      d       4
```

Combine `DataFrame` objects with overlapping columns and return everything. Columns outside the intersection will be filled with `NaN` values.

```
>>> df3 = pd.DataFrame([['c', 3, 'cat'], ['d', 4, 'dog']],
...                    columns=['letter', 'number', 'animal'])
>>> df3
  letter  number animal
0      c       3    cat
1      d       4    dog
>>> pd.concat([df1, df3], sort=False)
  letter  number animal
0      a       1    NaN
1      b       2    NaN
0      c       3    cat
1      d       4    dog
```

Combine `DataFrame` objects with overlapping columns and return only those that are shared by passing `inner` to the `join` keyword argument.

```
>>> pd.concat([df1, df3], join="inner")
  letter  number
0      a       1
1      b       2
0      c       3
1      d       4
```

Combine `DataFrame` objects horizontally along the x axis by passing in `axis=1`.

```
>>> df4 = pd.DataFrame([['bird', 'polly'], ['monkey', 'george']],
...                    columns=['animal', 'name'])
>>> pd.concat([df1, df4], axis=1)
  letter  number  animal    name
0      a       1    bird   polly
1      b       2  monkey  george
```

Prevent the result from including duplicate index values with the `verify_integrity` option.

```
>>> df5 = pd.DataFrame([1], index=['a'])
>>> df5
   0
a  1
>>> df6 = pd.DataFrame([2], index=['a'])
>>> df6
   0
a  2
>>> pd.concat([df5, df6], verify_integrity=True)
Traceback (most recent call last):
    ...
ValueError: Indexes have overlapping values: ['a']
```

pandas.get_dummies

pandas.**get_dummies**(*data*, *prefix=None*, *prefix_sep='_'*, *dummy_na=False*, *columns=None*, *sparse=False*, *drop_first=False*, *dtype=None*)

Convert categorical variable into dummy/indicator variables.

Parameters

data [array-like, Series, or DataFrame] Data of which to get dummy indicators.

prefix [str, list of str, or dict of str, default None] String to append DataFrame column names. Pass a list with length equal to the number of columns when calling get_dummies on a DataFrame. Alternatively, *prefix* can be a dictionary mapping column names to prefixes.

prefix_sep [str, default '_'] If appending prefix, separator/delimiter to use. Or pass a list or dictionary as with *prefix*.

dummy_na [bool, default False] Add a column to indicate NaNs, if False NaNs are ignored.

columns [list-like, default None] Column names in the DataFrame to be encoded. If *columns* is None then all the columns with *object* or *category* dtype will be converted.

sparse [bool, default False] Whether the dummy-encoded columns should be backed by a `SparseArray` (True) or a regular NumPy array (False).

drop_first [bool, default False] Whether to get k-1 dummies out of k categorical levels by removing the first level.

dtype [dtype, default np.uint8] Data type for new columns. Only a single dtype is allowed.

Returns

DataFrame Dummy-coded data.

See also:

Series.str.get_dummies Convert Series to dummy codes.

Examples

```
>>> s = pd.Series(list('abca'))
```

```
>>> pd.get_dummies(s)
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0
```

```
>>> s1 = ['a', 'b', np.nan]
```

```
>>> pd.get_dummies(s1)
   a  b
0  1  0
1  0  1
2  0  0
```

```
>>> pd.get_dummies(s1, dummy_na=True)
   a  b  NaN
0  1  0    0
1  0  1    0
2  0  0    1
```

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['b', 'a', 'c'],
...                    'C': [1, 2, 3]})
```

```
>>> pd.get_dummies(df, prefix=['col1', 'col2'])
   C  col1_a  col1_b  col2_a  col2_b  col2_c
0  1       1       0       0       1       0
1  2       0       1       1       0       0
2  3       1       0       0       0       1
```

```
>>> pd.get_dummies(pd.Series(list('abcaa')))
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0
4  1  0  0
```

```
>>> pd.get_dummies(pd.Series(list('abcaa')), drop_first=True)
   b  c
0  0  0
1  1  0
2  0  1
3  0  0
4  0  0
```

```
>>> pd.get_dummies(pd.Series(list('abc')), dtype=float)
     a    b    c
0  1.0  0.0  0.0
```

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```
1  0.0  1.0  0.0
2  0.0  0.0  1.0
```

pandas.factorize

pandas.**factorize**(*values*, *sort=False*, *na_sentinel=- 1*, *size_hint=None*)

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. *factorize* is available as both a top-level function *pandas.factorize()*, and as a method *Series.factorize()* and *Index.factorize()*.

Parameters

values [sequence] A 1-D sequence. Sequences that aren't pandas objects are coerced to ndarrays before factorization.

sort [bool, default False] Sort *uniques* and shuffle *codes* to maintain the relationship.

na_sentinel [int or None, default -1] Value to mark "not found". If None, will not drop the NaN from the uniques of the values.

Changed in version 1.1.2.

size_hint [int, optional] Hint to the hashtable sizer.

Returns

codes [ndarray] An integer ndarray that's an indexer into *uniques*. `uniques.take(codes)` will have the same values as *values*.

uniques [ndarray, Index, or Categorical] The unique valid values. When *values* is Categorical, *uniques* is a Categorical. When *values* is some other pandas object, an *Index* is returned. Otherwise, a 1-D ndarray is returned.

Note: Even if there's a missing value in *values*, *uniques* will *not* contain an entry for it.

See also:

cut Discretize continuous-valued array.

unique Find the unique value in an array.

Examples

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like *Series.factorize()*.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the *uniques* will be sorted, and *codes* will be shuffled so that the relationship is the maintained.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1]...)
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in *codes* with *na_sentinel* (`-1` by default). Note that missing values are never included in *uniques*.

```
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1,  1,  2,  0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we've only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of *uniques* will differ. For Categoricals, a *Categorical* is returned.

```
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
['a', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Notice that `'b'` is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
Index(['a', 'c'], dtype='object')
```

If NaN is in the values, and we want to include NaN in the uniques of the values, it can be achieved by setting `na_sentinel=None`.

```
>>> values = np.array([1, 2, 1, np.nan])
>>> codes, uniques = pd.factorize(values)  # default: na_sentinel=-1
>>> codes
array([ 0,  1,  0, -1])
>>> uniques
array([1., 2.])
```

```
>>> codes, uniques = pd.factorize(values, na_sentinel=None)
>>> codes
array([0, 1, 0, 2])
>>> uniques
array([ 1.,  2., nan])
```

pandas.unique

pandas.**unique**(*values*)

Hash table-based unique. Uniques are returned in order of appearance. This does NOT sort.

Significantly faster than numpy.unique. Includes NA values.

Parameters

values [1d array-like]

Returns

numpy.ndarray or ExtensionArray The return can be:

- Index : when the input is an Index
- Categorical : when the input is a Categorical dtype
- ndarray : when the input is a Series/ndarray

Return numpy.ndarray or ExtensionArray.

See also:

Index.unique Return unique values from an Index.

Series.unique Return unique values of Series object.

Examples

```
>>> pd.unique(pd.Series([2, 1, 3, 3]))
array([2, 1, 3])
```

```
>>> pd.unique(pd.Series([2] + [1] * 5))
array([2, 1])
```

```
>>> pd.unique(pd.Series([pd.Timestamp('20160101'),
...                      pd.Timestamp('20160101')]))
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
>>> pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
...                      pd.Timestamp('20160101', tz='US/Eastern')]))
array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],
      dtype=object)
```

```
>>> pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...                     pd.Timestamp('20160101', tz='US/Eastern')]))
DatetimeIndex(['2016-01-01 00:00:00-05:00'],
...           dtype='datetime64[ns, US/Eastern]', freq=None)
```

```
>>> pd.unique(list('baabc'))
array(['b', 'a', 'c'], dtype=object)
```

An unordered Categorical will return categories in the order of appearance.

```
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'))))
[b, a, c]
Categories (3, object): [b, a, c]
```

```
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'),
...                                    categories=list('abc'))))
[b, a, c]
Categories (3, object): [b, a, c]
```

An ordered Categorical preserves the category ordering.

```
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'),
...                                    categories=list('abc'),
...                                    ordered=True)))
[b, a, c]
Categories (3, object): [a < b < c]
```

An array of tuples

```
>>> pd.unique([('a', 'b'), ('b', 'a'), ('a', 'c'), ('b', 'a')])
array([('a', 'b'), ('b', 'a'), ('a', 'c')], dtype=object)
```

pandas.wide_to_long

pandas.**wide_to_long**(*df*, *stubnames*, *i*, *j*, *sep=''*, *suffix='\\d+'*)

Wide panel to long format. Less flexible but more user-friendly than melt.

With stubnames ['A', 'B'], this function expects to find one or more group of columns with format A-suffix1, A-suffix2,..., B-suffix1, B-suffix2,... You specify what you want to call this suffix in the resulting long format with *j* (for example *j='year'*)

Each row of these wide variables are assumed to be uniquely identified by *i* (can be a single column name or a list of column names)

All remaining variables in the data frame are left intact.

Parameters

df [DataFrame] The wide-format DataFrame.

stubnames [str or list-like] The stub name(s). The wide format variables are assumed to start with the stub names.

i [str or list-like] Column(s) to use as id variable(s).

j [str] The name of the sub-observation variable. What you wish to name your suffix in the long format.

sep [str, default ""] A character indicating the separation of the variable names in the wide format, to be stripped from the names in the long format. For example, if your column names are A-suffix1, A-suffix2, you can strip the hyphen by specifying *sep='-'*.

suffix [str, default '\d+'] A regular expression capturing the wanted suffixes. '\d+' captures numeric suffixes. Suffixes with no numbers could be specified with the negated character class '\D+'. You can also further disambiguate suffixes, for example, if your wide variables are of the form A-one, B-two,.., and you have an unrelated column A-rating, you can ignore the last one by specifying *suffix='(!?one|two)'*. When all suffixes are numeric, they are cast to int64/float64.

Returns

DataFrame A DataFrame that contains each stub name as a variable, with new index (i, j).

See also:

melt Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

pivot Create a spreadsheet-style pivot table as a DataFrame.

DataFrame.pivot Pivot without aggregation that can handle non-numeric data.

DataFrame.pivot_table Generalization of pivot that can handle duplicate values for one index/column pair.

DataFrame.unstack Pivot based on the index values instead of a column.

Notes

All extra variables are left untouched. This simply uses *pandas.melt* under the hood, but is hard-coded to "do the right thing" in a typical case.

Examples

```
>>> np.random.seed(123)
>>> df = pd.DataFrame({"A1970" : {0 : "a", 1 : "b", 2 : "c"},
...                    "A1980" : {0 : "d", 1 : "e", 2 : "f"},
...                    "B1970" : {0 : 2.5, 1 : 1.2, 2 : .7},
...                    "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1},
...                    "X"     : dict(zip(range(3), np.random.randn(3)))
...                   })
>>> df["id"] = df.index
>>> df
  A1970 A1980  B1970  B1980         X  id
0     a     d    2.5    3.2 -1.085631   0
1     b     e    1.2    1.3  0.997345   1
2     c     f    0.7    0.1  0.282978   2
>>> pd.wide_to_long(df, ["A", "B"], i="id", j="year")
...
                X  A    B
id year
0  1970 -1.085631  a  2.5
1  1970  0.997345  b  1.2
2  1970  0.282978  c  0.7
0  1980 -1.085631  d  3.2
1  1980  0.997345  e  1.3
2  1980  0.282978  f  0.1
```

With multiple id columns

```
>>> df = pd.DataFrame({
...     'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],
...     'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],
...     'ht1': [2.8, 2.9, 2.2, 2, 1.8, 1.9, 2.2, 2.3, 2.1],
...     'ht2': [3.4, 3.8, 2.9, 3.2, 2.8, 2.4, 3.3, 3.4, 2.9]
... })
>>> df
   famid  birth  ht1  ht2
0      1      1  2.8  3.4
1      1      2  2.9  3.8
2      1      3  2.2  2.9
3      2      1  2.0  3.2
4      2      2  1.8  2.8
```

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```
5       2       3  1.9  2.4
6       3       1  2.2  3.3
7       3       2  2.3  3.4
8       3       3  2.1  2.9
>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], j='age')
>>> l
...
                  ht
famid birth age
1     1     1    2.8
            2    3.4
      2     1    2.9
            2    3.8
      3     1    2.2
            2    2.9
2     1     1    2.0
            2    3.2
      2     1    1.8
            2    2.8
      3     1    1.9
            2    2.4
3     1     1    2.2
            2    3.3
      2     1    2.3
            2    3.4
      3     1    2.1
            2    2.9
```

Going from long back to wide just takes some creative use of *unstack*

```
>>> w = l.unstack()
>>> w.columns = w.columns.map('{0[0]}{0[1]}'.format)
>>> w.reset_index()
   famid  birth  ht1  ht2
0      1      1  2.8  3.4
1      1      2  2.9  3.8
2      1      3  2.2  2.9
3      2      1  2.0  3.2
4      2      2  1.8  2.8
5      2      3  1.9  2.4
6      3      1  2.2  3.3
7      3      2  2.3  3.4
8      3      3  2.1  2.9
```

Less wieldy column names are also handled

```
>>> np.random.seed(0)
>>> df = pd.DataFrame({'A(weekly)-2010': np.random.rand(3),
...                    'A(weekly)-2011': np.random.rand(3),
...                    'B(weekly)-2010': np.random.rand(3),
...                    'B(weekly)-2011': np.random.rand(3),
...                    'X' : np.random.randint(3, size=3)})
>>> df['id'] = df.index
>>> df
   A(weekly)-2010  A(weekly)-2011  B(weekly)-2010  B(weekly)-2011  X  id
0        0.548814        0.544883        0.437587        0.383442  0   0
1        0.715189        0.423655        0.891773        0.791725  1   1
```

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```
2        0.602763        0.645894        0.963663        0.528895  1    2
```

```
>>> pd.wide_to_long(df, ['A(weekly)', 'B(weekly)'], i='id',
...                 j='year', sep='-')
...
         X  A(weekly)  B(weekly)
id year
0  2010  0   0.548814   0.437587
1  2010  1   0.715189   0.891773
2  2010  1   0.602763   0.963663
0  2011  0   0.544883   0.383442
1  2011  1   0.423655   0.791725
2  2011  1   0.645894   0.528895
```

If we have many columns, we could also use a regex to find our stubnames and pass that list on to wide_to_long

```
>>> stubnames = sorted(
...     set([match[0] for match in df.columns.str.findall(
...         r'[A-B]\(.*\)').values if match != []])
... )
>>> list(stubnames)
['A(weekly)', 'B(weekly)']
```

All of the above examples have integers as suffixes. It is possible to have non-integers as suffixes.

```
>>> df = pd.DataFrame({
...     'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],
...     'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],
...     'ht_one': [2.8, 2.9, 2.2, 2, 1.8, 1.9, 2.2, 2.3, 2.1],
...     'ht_two': [3.4, 3.8, 2.9, 3.2, 2.8, 2.4, 3.3, 3.4, 2.9]
... })
>>> df
   famid  birth  ht_one  ht_two
0      1      1     2.8     3.4
1      1      2     2.9     3.8
2      1      3     2.2     2.9
3      2      1     2.0     3.2
4      2      2     1.8     2.8
5      2      3     1.9     2.4
6      3      1     2.2     3.3
7      3      2     2.3     3.4
8      3      3     2.1     2.9
```

```
>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], j='age',
...                     sep='_', suffix=r'\w+')
>>> l
...
                ht
famid birth age
1     1     one  2.8
            two  3.4
      2     one  2.9
            two  3.8
      3     one  2.2
            two  2.9
2     1     one  2.0
```

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```
              two  3.2
      2       one  1.8
              two  2.8
      3       one  1.9
              two  2.4
3     1       one  2.2
              two  3.3
      2       one  2.3
              two  3.4
      3       one  2.1
              two  2.9
```

3.2.2 Top-level missing data

isna(obj)	Detect missing values for an array-like object.
isnull(obj)	Detect missing values for an array-like object.
notna(obj)	Detect non-missing values for an array-like object.
notnull(obj)	Detect non-missing values for an array-like object.

pandas.isna

pandas.**isna**(*obj*)

Detect missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are missing (NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

Parameters

obj [scalar or array-like] Object to check for null or missing values.

Returns

bool or array-like of bool For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

See also:

notna Boolean inverse of pandas.isna.

Series.isna Detect missing values in a Series.

DataFrame.isna Detect missing values in a DataFrame.

Index.isna Detect missing values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.isna('dog')
False
```

```
>>> pd.isna(pd.NA)
True
```

```
>>> pd.isna(np.nan)
True
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan,  3.],
       [ 4.,  5., nan]])
>>> pd.isna(array)
array([[False,  True, False],
       [False, False,  True]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                           "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
              dtype='datetime64[ns]', freq=None)
>>> pd.isna(index)
array([False, False,  True, False])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
     0     1    2
0  ant   bee  cat
1  dog  None  fly
>>> pd.isna(df)
       0      1      2
0  False  False  False
1  False   True  False
```

```
>>> pd.isna(df[1])
0    False
1     True
Name: 1, dtype: bool
```

pandas.isnull

pandas.**isnull**(*obj*)

Detect missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are missing (`NaN` in numeric arrays, `None` or `NaN` in object arrays, `NaT` in datetimelike).

Parameters

obj [scalar or array-like] Object to check for null or missing values.

Returns

bool or array-like of bool For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

See also:

notna Boolean inverse of pandas.isna.

Series.isna Detect missing values in a Series.

DataFrame.isna Detect missing values in a DataFrame.

Index.isna Detect missing values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.isna('dog')
False
```

```
>>> pd.isna(pd.NA)
True
```

```
>>> pd.isna(np.nan)
True
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan,  3.],
       [ 4.,  5., nan]])
>>> pd.isna(array)
array([[False,  True, False],
       [False, False,  True]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                           "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
              dtype='datetime64[ns]', freq=None)
>>> pd.isna(index)
array([False, False,  True, False])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
     0     1    2
0  ant   bee  cat
1  dog  None  fly
>>> pd.isna(df)
       0      1      2
0  False  False  False
1  False   True  False
```

```
>>> pd.isna(df[1])
0    False
1     True
Name: 1, dtype: bool
```

pandas.notna

pandas.**notna**(*obj*)

Detect non-missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

Parameters

obj [array-like or object value] Object to check for *not* null or *non*-missing values.

Returns

bool or array-like of bool For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

See also:

isna Boolean inverse of pandas.notna.

Series.notna Detect valid values in a Series.

DataFrame.notna Detect valid values in a DataFrame.

Index.notna Detect valid values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.notna('dog')
True
```

```
>>> pd.notna(pd.NA)
False
```

```
>>> pd.notna(np.nan)
False
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan,  3.],
       [ 4.,  5., nan]])
>>> pd.notna(array)
array([[ True, False,  True],
       [ True,  True, False]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                           "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
              dtype='datetime64[ns]', freq=None)
>>> pd.notna(index)
array([ True,  True, False,  True])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
     0     1    2
0  ant   bee  cat
1  dog  None  fly
>>> pd.notna(df)
      0      1     2
0  True   True  True
1  True  False  True
```

```
>>> pd.notna(df[1])
0     True
1    False
Name: 1, dtype: bool
```

pandas.notnull

pandas.**notnull**(*obj*)

Detect non-missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

Parameters

obj [array-like or object value] Object to check for *not* null or *non*-missing values.

Returns

bool or array-like of bool For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

See also:

isna Boolean inverse of pandas.notna.

Series.notna Detect valid values in a Series.

DataFrame.notna Detect valid values in a DataFrame.

Index.notna Detect valid values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.notna('dog')
True
```

```
>>> pd.notna(pd.NA)
False
```

```
>>> pd.notna(np.nan)
False
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan,  3.],
       [ 4.,  5., nan]])
>>> pd.notna(array)
array([[ True, False,  True],
       [ True,  True, False]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                           "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
              dtype='datetime64[ns]', freq=None)
>>> pd.notna(index)
array([ True,  True, False,  True])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
     0     1    2
0  ant   bee  cat
1  dog  None  fly
>>> pd.notna(df)
      0      1     2
0  True   True  True
1  True  False  True
```

```
>>> pd.notna(df[1])
0     True
1    False
Name: 1, dtype: bool
```

3.2.3 Top-level conversions

to_numeric(arg[, errors, downcast])	Convert argument to a numeric type.

pandas.to_numeric

pandas.**to_numeric**(*arg*, *errors='raise'*, *downcast=None*)

Convert argument to a numeric type.

The default return dtype is *float64* or *int64* depending on the data supplied. Use the *downcast* parameter to obtain other dtypes.

Please note that precision loss may occur if really large numbers are passed in. Due to the internal limitations of *ndarray*, if numbers smaller than *-9223372036854775808* (np.iinfo(np.int64).min) or larger than *18446744073709551615* (np.iinfo(np.uint64).max) are passed in, it is very likely they will be converted to float so that they can stored in an *ndarray*. These warnings apply similarly to *Series* since it internally leverages *ndarray*.

Parameters

arg [scalar, list, tuple, 1-d array, or Series] Argument to be converted.

errors [{'ignore', 'raise', 'coerce'}, default 'raise']

- If 'raise', then invalid parsing will raise an exception.
- If 'coerce', then invalid parsing will be set as NaN.
- If 'ignore', then invalid parsing will return the input.

downcast [{'integer', 'signed', 'unsigned', 'float'}, default None] If not None, and if the data has been successfully cast to a numerical dtype (or if the data was numeric to begin with), downcast that resulting data to the smallest numerical dtype possible according to the following rules:

- 'integer' or 'signed': smallest signed int dtype (min.: np.int8)
- 'unsigned': smallest unsigned int dtype (min.: np.uint8)
- 'float': smallest float dtype (min.: np.float32)

As this behaviour is separate from the core conversion to numeric values, any errors raised during the downcasting will be surfaced regardless of the value of the 'errors' input.

In addition, downcasting will only occur if the size of the resulting data's dtype is strictly larger than the dtype it is to be cast to, so if none of the dtypes checked satisfy that specification, no downcasting will be performed on the data.

Returns

ret Numeric if parsing succeeded. Return type depends on input. Series if Series, otherwise ndarray.

See also:

DataFrame.astype Cast argument to a specified dtype.

to_datetime Convert argument to datetime.

to_timedelta Convert argument to timedelta.

numpy.ndarray.astype Cast a numpy array to a specified type.

DataFrame.convert_dtypes Convert dtypes.

Examples

Take separate series and convert to numeric, coercing when told to

```
>>> s = pd.Series(['1.0', '2', -3])
>>> pd.to_numeric(s)
0    1.0
1    2.0
2   -3.0
dtype: float64
>>> pd.to_numeric(s, downcast='float')
0    1.0
1    2.0
2   -3.0
dtype: float32
>>> pd.to_numeric(s, downcast='signed')
0    1
1    2
2   -3
dtype: int8
>>> s = pd.Series(['apple', '1.0', '2', -3])
>>> pd.to_numeric(s, errors='ignore')
0    apple
1      1.0
2        2
3       -3
dtype: object
>>> pd.to_numeric(s, errors='coerce')
0    NaN
1    1.0
2    2.0
3   -3.0
dtype: float64
```

3.2.4 Top-level dealing with datetimelike

to_datetime(arg[, errors, dayfirst, ...])	Convert argument to datetime.
to_timedelta(arg[, unit, errors])	Convert argument to timedelta.
date_range([start, end, periods, freq, tz, ...])	Return a fixed frequency DatetimeIndex.
bdate_range([start, end, periods, freq, tz, ...])	Return a fixed frequency DatetimeIndex, with business day as the default frequency.
period_range([start, end, periods, freq, name])	Return a fixed frequency PeriodIndex.
timedelta_range([start, end, periods, freq, ...])	Return a fixed frequency TimedeltaIndex, with day as the default frequency.
infer_freq(index[, warn])	Infer the most likely frequency given the input index.

pandas.to_datetime

pandas.**to_datetime**(*arg*, *errors='raise'*, *dayfirst=False*, *yearfirst=False*, *utc=None*, *format=None*, *exact=True*, *unit=None*, *infer_datetime_format=False*, *origin='unix'*, *cache=True*)

Convert argument to datetime.

Parameters

arg [int, float, str, datetime, list, tuple, 1-d array, Series, DataFrame/dict-like] The object to convert to a datetime.

errors [{'ignore', 'raise', 'coerce'}, default 'raise']

- If 'raise', then invalid parsing will raise an exception.
- If 'coerce', then invalid parsing will be set as NaT.
- If 'ignore', then invalid parsing will return the input.

dayfirst [bool, default False] Specify a date parse order if *arg* is str or its list-likes. If True, parses dates with the day first, eg 10/11/12 is parsed as 2012-11-10. Warning: dayfirst=True is not strict, but will prefer to parse with day first (this is a known bug, based on dateutil behavior).

yearfirst [bool, default False] Specify a date parse order if *arg* is str or its list-likes.

- If True parses dates with the year first, eg 10/11/12 is parsed as 2010-11-12.
- If both dayfirst and yearfirst are True, yearfirst is preceded (same as dateutil).

Warning: yearfirst=True is not strict, but will prefer to parse with year first (this is a known bug, based on dateutil behavior).

utc [bool, default None] Return UTC DatetimeIndex if True (converting any tz-aware datetime.datetime objects as well).

format [str, default None] The strftime to parse time, eg "%d/%m/%Y", note that "%f" will parse all the way up to nanoseconds. See strftime documentation for more information on choices: https://docs.python.org/3/library/datetime.html#strftime-and-strptime-behavior.

exact [bool, True by default] Behaves as: - If True, require an exact format match. - If False, allow the format to match anywhere in the target string.

unit [str, default 'ns'] The unit of the arg (D,s,ms,us,ns) denote the unit, which is an integer or float number. This will be based off the origin. Example, with unit='ms' and origin='unix' (the default), this would calculate the number of milliseconds to the unix epoch start.

infer_datetime_format [bool, default False] If True and no *format* is given, attempt to infer the format of the datetime strings based on the first non-NaN element, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.

origin [scalar, default 'unix'] Define the reference date. The numeric values would be parsed as number of units (defined by *unit*) since this reference date.

- If 'unix' (or POSIX) time; origin is set to 1970-01-01.
- If 'julian', unit must be 'D', and origin is set to beginning of Julian Calendar. Julian day number 0 is assigned to the day starting at noon on January 1, 4713 BC.
- If Timestamp convertible, origin is set to Timestamp identified by origin.

cache [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets. The cache is only used when there are at least 50 values.

The presence of out-of-bounds values will render the cache unusable and may slow down parsing.

Changed in version 0.25.0: - changed default value from False to True.

Returns

datetime If parsing succeeded. Return type depends on input:

- list-like: DatetimeIndex
- Series: Series of datetime64 dtype
- scalar: Timestamp

In case when it is not possible to return designated types (e.g. when any element of input is before Timestamp.min or after Timestamp.max) return will have datetime.datetime type (or corresponding array/Series).

See also:

DataFrame.astype Cast argument to a specified dtype.

to_timedelta Convert argument to timedelta.

convert_dtypes Convert dtypes.

Examples

Assembling a datetime from multiple columns of a DataFrame. The keys can be common abbreviations like ['year', 'month', 'day', 'minute', 'second', 'ms', 'us', 'ns']) or plurals of the same

```
>>> df = pd.DataFrame({'year': [2015, 2016],
...                    'month': [2, 3],
...                    'day': [4, 5]})
>>> pd.to_datetime(df)
0   2015-02-04
1   2016-03-05
dtype: datetime64[ns]
```

If a date does not meet the timestamp limitations, passing errors='ignore' will return the original input instead of raising any exception.

Passing errors='coerce' will force an out-of-bounds date to NaT, in addition to forcing non-dates (or non-parseable dates) to NaT.

```
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='ignore')
datetime.datetime(1300, 1, 1, 0, 0)
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='coerce')
NaT
```

Passing infer_datetime_format=True can often-times speedup a parsing if its not an ISO8601 format exactly, but in a regular format.

```
>>> s = pd.Series(['3/11/2000', '3/12/2000', '3/13/2000'] * 1000)
>>> s.head()
0    3/11/2000
1    3/12/2000
2    3/13/2000
3    3/11/2000
```

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```
4    3/12/2000
dtype: object
```

```
>>> %timeit pd.to_datetime(s, infer_datetime_format=True)
100 loops, best of 3: 10.4 ms per loop
```

```
>>> %timeit pd.to_datetime(s, infer_datetime_format=False)
1 loop, best of 3: 471 ms per loop
```

Using a unix epoch time

```
>>> pd.to_datetime(1490195805, unit='s')
Timestamp('2017-03-22 15:16:45')
>>> pd.to_datetime(1490195805433502912, unit='ns')
Timestamp('2017-03-22 15:16:45.433502912')
```

Warning: For float arg, precision rounding might happen. To prevent unexpected behavior use a fixed-width exact type.

Using a non-unix epoch origin

```
>>> pd.to_datetime([1, 2, 3], unit='D',
...                origin=pd.Timestamp('1960-01-01'))
DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype='datetime64[ns]',␣
↪freq=None)
```

pandas.to_timedelta

pandas.**to_timedelta**(*arg*, *unit=None*, *errors='raise'*)

Convert argument to timedelta.

Timedeltas are absolute differences in times, expressed in difference units (e.g. days, hours, minutes, seconds). This method converts an argument from a recognized timedelta format / value into a Timedelta type.

Parameters

arg [str, timedelta, list-like or Series] The data to be converted to timedelta.

Deprecated since version 1.2: Strings with units 'M', 'Y' and 'y' do not represent unambiguous timedelta values and will be removed in a future version

unit [str, optional] Denotes the unit of the arg for numeric *arg*. Defaults to `"ns"`.

Possible values:

- 'W'
- 'D' / 'days' / 'day'
- 'hours' / 'hour' / 'hr' / 'h'
- 'm' / 'minute' / 'min' / 'minutes' / 'T'
- 'S' / 'seconds' / 'sec' / 'second'
- 'ms' / 'milliseconds' / 'millisecond' / 'milli' / 'millis' / 'L'

- 'us' / 'microseconds' / 'microsecond' / 'micro' / 'micros' / 'U'
- 'ns' / 'nanoseconds' / 'nano' / 'nanos' / 'nanosecond' / 'N'

Changed in version 1.1.0: Must not be specified when *arg* context strings and `errors="raise"`.

errors [{'ignore', 'raise', 'coerce'}, default 'raise']

- If 'raise', then invalid parsing will raise an exception.
- If 'coerce', then invalid parsing will be set as NaT.
- If 'ignore', then invalid parsing will return the input.

Returns

timedelta64 or numpy.array of timedelta64 Output type returned if parsing succeeded.

See also:

DataFrame.astype Cast argument to a specified dtype.

to_datetime Convert argument to datetime.

convert_dtypes Convert dtypes.

Notes

If the precision is higher than nanoseconds, the precision of the duration is truncated to nanoseconds for string inputs.

Examples

Parsing a single string to a Timedelta:

```
>>> pd.to_timedelta('1 days 06:05:01.00003')
Timedelta('1 days 06:05:01.000030')
>>> pd.to_timedelta('15.5us')
Timedelta('0 days 00:00:00.000015500')
```

Parsing a list or array of strings:

```
>>> pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015500', NaT],
               dtype='timedelta64[ns]', freq=None)
```

Converting numbers by specifying the *unit* keyword argument:

```
>>> pd.to_timedelta(np.arange(5), unit='s')
TimedeltaIndex(['0 days 00:00:00', '0 days 00:00:01', '0 days 00:00:02',
                '0 days 00:00:03', '0 days 00:00:04'],
               dtype='timedelta64[ns]', freq=None)
>>> pd.to_timedelta(np.arange(5), unit='d')
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq=None)
```

pandas.date_range

pandas.**date_range**(*start=None*, *end=None*, *periods=None*, *freq=None*, *tz=None*, *normalize=False*, *name=None*, *closed=None*, ***kwargs*)

Return a fixed frequency DatetimeIndex.

Parameters

start [str or datetime-like, optional] Left bound for generating dates.

end [str or datetime-like, optional] Right bound for generating dates.

periods [int, optional] Number of periods to generate.

freq [str or DateOffset, default 'D'] Frequency strings can have multiples, e.g. '5H'. See *here* for a list of frequency aliases.

tz [str or tzinfo, optional] Time zone name for returning localized DatetimeIndex, for example 'Asia/Hong_Kong'. By default, the resulting DatetimeIndex is timezone-naive.

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

name [str, default None] Name of the resulting DatetimeIndex.

closed [{None, 'left', 'right'}, optional] Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None, the default).

****kwargs** For compatibility. Has no effect on the result.

Returns

rng [DatetimeIndex]

See also:

DatetimeIndex An immutable container for datetimes.

timedelta_range Return a fixed frequency TimedeltaIndex.

period_range Return a fixed frequency PeriodIndex.

interval_range Return a fixed frequency IntervalIndex.

Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting `DatetimeIndex` will have `periods` linearly spaced elements between `start` and `end` (closed on both sides).

To learn more about the frequency strings, please see this link.

Examples

Specifying the values

The next four examples generate the same *DatetimeIndex*, but vary the combination of *start*, *end* and *periods*.

Specify *start* and *end*, with the default daily frequency.

```
>>> pd.date_range(start='1/1/2018', end='1/08/2018')
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05', '2018-01-06', '2018-01-07', '2018-01-08'],
              dtype='datetime64[ns]', freq='D')
```

Specify *start* and *periods*, the number of periods (days).

```
>>> pd.date_range(start='1/1/2018', periods=8)
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05', '2018-01-06', '2018-01-07', '2018-01-08'],
              dtype='datetime64[ns]', freq='D')
```

Specify *end* and *periods*, the number of periods (days).

```
>>> pd.date_range(end='1/1/2018', periods=8)
DatetimeIndex(['2017-12-25', '2017-12-26', '2017-12-27', '2017-12-28',
               '2017-12-29', '2017-12-30', '2017-12-31', '2018-01-01'],
              dtype='datetime64[ns]', freq='D')
```

Specify *start*, *end*, and *periods*; the frequency is generated automatically (linearly spaced).

```
>>> pd.date_range(start='2018-04-24', end='2018-04-27', periods=3)
DatetimeIndex(['2018-04-24 00:00:00', '2018-04-25 12:00:00',
               '2018-04-27 00:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Other Parameters

Changed the *freq* (frequency) to `'M'` (month end frequency).

```
>>> pd.date_range(start='1/1/2018', periods=5, freq='M')
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31', '2018-04-30',
               '2018-05-31'],
              dtype='datetime64[ns]', freq='M')
```

Multiples are allowed

```
>>> pd.date_range(start='1/1/2018', periods=5, freq='3M')
DatetimeIndex(['2018-01-31', '2018-04-30', '2018-07-31', '2018-10-31',
               '2019-01-31'],
              dtype='datetime64[ns]', freq='3M')
```

freq can also be specified as an Offset object.

```
>>> pd.date_range(start='1/1/2018', periods=5, freq=pd.offsets.MonthEnd(3))
DatetimeIndex(['2018-01-31', '2018-04-30', '2018-07-31', '2018-10-31',
               '2019-01-31'],
              dtype='datetime64[ns]', freq='3M')
```

Specify *tz* to set the timezone.

```
>>> pd.date_range(start='1/1/2018', periods=5, tz='Asia/Tokyo')
DatetimeIndex(['2018-01-01 00:00:00+09:00', '2018-01-02 00:00:00+09:00',
               '2018-01-03 00:00:00+09:00', '2018-01-04 00:00:00+09:00',
               '2018-01-05 00:00:00+09:00'],
              dtype='datetime64[ns, Asia/Tokyo]', freq='D')
```

closed controls whether to include *start* and *end* that are on the boundary. The default includes boundary points on either end.

```
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed=None)
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03', '2017-01-04'],
              dtype='datetime64[ns]', freq='D')
```

Use `closed='left'` to exclude *end* if it falls on the boundary.

```
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='left')
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03'],
              dtype='datetime64[ns]', freq='D')
```

Use `closed='right'` to exclude *start* if it falls on the boundary.

```
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='right')
DatetimeIndex(['2017-01-02', '2017-01-03', '2017-01-04'],
              dtype='datetime64[ns]', freq='D')
```

pandas.bdate_range

pandas.**bdate_range**(*start=None*, *end=None*, *periods=None*, *freq='B'*, *tz=None*, *normalize=True*, *name=None*, *weekmask=None*, *holidays=None*, *closed=None*, ***kwargs*)

Return a fixed frequency DatetimeIndex, with business day as the default frequency.

Parameters

start [str or datetime-like, default None] Left bound for generating dates.

end [str or datetime-like, default None] Right bound for generating dates.

periods [int, default None] Number of periods to generate.

freq [str or DateOffset, default 'B' (business daily)] Frequency strings can have multiples, e.g. '5H'.

tz [str or None] Time zone name for returning localized DatetimeIndex, for example Asia/Beijing.

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

name [str, default None] Name of the resulting DatetimeIndex.

weekmask [str or None, default None] Weekmask of valid business days, passed to `numpy.busdaycalendar`, only used when custom frequency strings are passed. The default value None is equivalent to 'Mon Tue Wed Thu Fri'.

holidays [list-like or None, default None] Dates to exclude from the set of valid business days, passed to `numpy.busdaycalendar`, only used when custom frequency strings are passed.

closed [str, default None] Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None).

****kwargs** For compatibility. Has no effect on the result.

Returns

DatetimeIndex

Notes

Of the four parameters: `start`, `end`, `periods`, and `freq`, exactly three must be specified. Specifying `freq` is a requirement for `bdate_range`. Use `date_range` if specifying `freq` is not desired.

To learn more about the frequency strings, please see this link.

Examples

Note how the two weekend days are skipped in the result.

```
>>> pd.bdate_range(start='1/1/2018', end='1/08/2018')
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05', '2018-01-08'],
              dtype='datetime64[ns]', freq='B')
```

pandas.period_range

pandas.**period_range**(*start=None*, *end=None*, *periods=None*, *freq=None*, *name=None*)

Return a fixed frequency PeriodIndex.

The day (calendar) is the default frequency.

Parameters

start [str or period-like, default None] Left bound for generating periods.

end [str or period-like, default None] Right bound for generating periods.

periods [int, default None] Number of periods to generate.

freq [str or DateOffset, optional] Frequency alias. By default the freq is taken from *start* or *end* if those are Period objects. Otherwise, the default is `"D"` for daily frequency.

name [str, default None] Name of the resulting PeriodIndex.

Returns

PeriodIndex

Notes

Of the three parameters: `start`, `end`, and `periods`, exactly two must be specified.

To learn more about the frequency strings, please see this link.

Examples

```
>>> pd.period_range(start='2017-01-01', end='2018-01-01', freq='M')
PeriodIndex(['2017-01', '2017-02', '2017-03', '2017-04', '2017-05', '2017-06',
             '2017-07', '2017-08', '2017-09', '2017-10', '2017-11', '2017-12',
             '2018-01'],
            dtype='period[M]', freq='M')
```

If `start` or `end` are `Period` objects, they will be used as anchor endpoints for a `PeriodIndex` with frequency matching that of the `period_range` constructor.

```
>>> pd.period_range(start=pd.Period('2017Q1', freq='Q'),
...                 end=pd.Period('2017Q2', freq='Q'), freq='M')
PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'],
            dtype='period[M]', freq='M')
```

pandas.timedelta_range

pandas.**timedelta_range**(*start=None*, *end=None*, *periods=None*, *freq=None*, *name=None*, *closed=None*)

Return a fixed frequency TimedeltaIndex, with day as the default frequency.

Parameters

start [str or timedelta-like, default None] Left bound for generating timedeltas.

end [str or timedelta-like, default None] Right bound for generating timedeltas.

periods [int, default None] Number of periods to generate.

freq [str or DateOffset, default 'D'] Frequency strings can have multiples, e.g. '5H'.

name [str, default None] Name of the resulting TimedeltaIndex.

closed [str, default None] Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None).

Returns

rng [TimedeltaIndex]

Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting `TimedeltaIndex` will have `periods` linearly spaced elements between `start` and `end` (closed on both sides).

To learn more about the frequency strings, please see this link.

Examples

```
>>> pd.timedelta_range(start='1 day', periods=4)
TimedeltaIndex(['1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `closed` parameter specifies which endpoint is included. The default behavior is to include both endpoints.

```
>>> pd.timedelta_range(start='1 day', periods=4, closed='right')
TimedeltaIndex(['2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `freq` parameter specifies the frequency of the TimedeltaIndex. Only fixed frequencies can be passed, non-fixed frequencies such as 'M' (month end) will raise.

```
>>> pd.timedelta_range(start='1 day', end='2 days', freq='6H')
TimedeltaIndex(['1 days 00:00:00', '1 days 06:00:00', '1 days 12:00:00',
                '1 days 18:00:00', '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='6H')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```
>>> pd.timedelta_range(start='1 day', end='5 days', periods=4)
TimedeltaIndex(['1 days 00:00:00', '2 days 08:00:00', '3 days 16:00:00',
                '5 days 00:00:00'],
               dtype='timedelta64[ns]', freq=None)
```

pandas.infer_freq

pandas.**infer_freq**(*index*, *warn=True*)

Infer the most likely frequency given the input index. If the frequency is uncertain, a warning will be printed.

Parameters

index [DatetimeIndex or TimedeltaIndex] If passed a Series will use the values of the series (NOT THE INDEX).

warn [bool, default True]

Returns

str or None None if no discernible frequency.

Raises

TypeError If the index is not datetime-like.

ValueError If there are fewer than three values.

3.2.5 Top-level dealing with intervals

interval_range([start, end, periods, freq, ...])	Return a fixed frequency IntervalIndex.

pandas.interval_range

pandas.**interval_range**(*start=None*, *end=None*, *periods=None*, *freq=None*, *name=None*, *closed='right'*)

Return a fixed frequency IntervalIndex.

Parameters

start [numeric or datetime-like, default None] Left bound for generating intervals.

end [numeric or datetime-like, default None] Right bound for generating intervals.

periods [int, default None] Number of periods to generate.

freq [numeric, str, or DateOffset, default None] The length of each interval. Must be consistent with the type of start and end, e.g. 2 for numeric, or '5H' for datetime-like. Default is 1 for numeric and 'D' for datetime-like.

name [str, default None] Name of the resulting IntervalIndex.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

Returns

IntervalIndex

See also:

IntervalIndex An Index of intervals that are all closed on the same side.

Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting `IntervalIndex` will have `periods` linearly spaced elements between `start` and `end`, inclusively.

To learn more about datetime-like frequency strings, please see this link.

Examples

Numeric `start` and `end` is supported.

```
>>> pd.interval_range(start=0, end=5)
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]],
              closed='right', dtype='interval[int64]')
```

Additionally, datetime-like input is also supported.

```
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
...                   end=pd.Timestamp('2017-01-04'))
IntervalIndex([(2017-01-01, 2017-01-02], (2017-01-02, 2017-01-03],
```

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```
              (2017-01-03, 2017-01-04]],
             closed='right', dtype='interval[datetime64[ns]]')
```

The `freq` parameter specifies the frequency between the left and right. endpoints of the individual intervals within the `IntervalIndex`. For numeric `start` and `end`, the frequency must also be numeric.

```
>>> pd.interval_range(start=0, periods=4, freq=1.5)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]],
              closed='right', dtype='interval[float64]')
```

Similarly, for datetime-like `start` and `end`, the frequency must be convertible to a DateOffset.

```
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
...                   periods=3, freq='MS')
IntervalIndex([(2017-01-01, 2017-02-01], (2017-02-01, 2017-03-01],
               (2017-03-01, 2017-04-01]],
              closed='right', dtype='interval[datetime64[ns]]')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```
>>> pd.interval_range(start=0, end=6, periods=4)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]],
          closed='right',
          dtype='interval[float64]')
```

The `closed` parameter specifies which endpoints of the individual intervals within the `IntervalIndex` are closed.

```
>>> pd.interval_range(end=5, periods=4, closed='both')
IntervalIndex([[1, 2], [2, 3], [3, 4], [4, 5]],
              closed='both', dtype='interval[int64]')
```

3.2.6 Top-level evaluation

eval(expr[, parser, engine, truediv, ...])	Evaluate a Python expression as a string using various backends.

pandas.eval

pandas.**eval**(*expr*, *parser='pandas'*, *engine=None*, *truediv=<object object>*, *local_dict=None*, *global_dict=None*, *resolvers=()*, *level=0*, *target=None*, *inplace=False*)

Evaluate a Python expression as a string using various backends.

The following arithmetic operations are supported: `+`, `-`, `*`, `/`, `**`, `%`, `//` (python engine only) along with the following boolean operations: `|` (or), `&` (and), and `~` (not). Additionally, the `'pandas'` parser allows the use of `and`, `or`, and `not` with the same semantics as the corresponding bitwise operators. *Series* and *DataFrame* objects are supported and behave as they would with plain ol' Python evaluation.

Parameters

expr [str] The expression to evaluate. This string cannot contain any Python statements, only Python expressions.

parser [{'pandas', 'python'}, default 'pandas'] The parser to use to construct the syntax tree

from the expression. The default of `'pandas'` parses code slightly different than standard Python. Alternatively, you can parse an expression using the `'python'` parser to retain strict Python semantics. See the *enhancing performance* documentation for more details.

engine [{'python', 'numexpr'}, default 'numexpr'] The engine used to evaluate the expression. Supported engines are

- None : tries to use `numexpr`, falls back to `python`
- **`'numexpr'`: This default engine evaluates pandas objects using** numexpr for large speed ups in complex expressions with large frames.
- **`'python'`: Performs operations as if you had `eval`'d in top** level python. This engine is generally not that useful.

More backends may be available in the future.

truediv [bool, optional] Whether to use true division, like in Python >= 3.

Deprecated since version 1.0.0.

local_dict [dict or None, optional] A dictionary of local variables, taken from locals() by default.

global_dict [dict or None, optional] A dictionary of global variables, taken from globals() by default.

resolvers [list of dict-like or None, optional] A list of objects implementing the `__getitem__` special method that you can use to inject an additional collection of namespaces to use for variable lookup. For example, this is used in the *`query()`* method to inject the `DataFrame.index` and `DataFrame.columns` variables that refer to their respective *`DataFrame`* instance attributes.

level [int, optional] The number of prior stack frames to traverse and add to the current scope. Most users will **not** need to change this parameter.

target [object, optional, default None] This is the target object for assignment. It is used when there is variable assignment in the expression. If so, then *target* must support item assignment with string keys, and if a copy is being returned, it must also support *.copy()*.

inplace [bool, default False] If *target* is provided, and the expression mutates *target*, whether to modify *target* inplace. Otherwise, return a copy of *target* with the mutation.

Returns

ndarray, numeric scalar, DataFrame, Series, or None The completion value of evaluating the given code or None if `inplace=True`.

Raises

ValueError There are many instances where such an error can be raised:

- *target=None*, but the expression is multiline.
- The expression is multiline, but not all them have item assignment. An example of such an arrangement is this:

  a = b + 1 a + 2

  Here, there are expressions on different lines, making it multiline, but the last line has no variable assigned to the output of *a + 2*.
- *inplace=True*, but the expression is missing item assignment.
- Item assignment is provided, but the *target* does not support string item assignment.

- Item assignment is provided and *inplace=False*, but the *target* does not support the *.copy()* method

See also:

`DataFrame.query` Evaluates a boolean expression to query the columns of a frame.

`DataFrame.eval` Evaluate a string describing operations on DataFrame columns.

Notes

The `dtype` of any objects involved in an arithmetic `%` operation are recursively cast to `float64`.

See the *enhancing performance* documentation for more details.

Examples

```
>>> df = pd.DataFrame({"animal": ["dog", "pig"], "age": [10, 20]})
>>> df
  animal  age
0    dog   10
1    pig   20
```

We can add a new column using `pd.eval`:

```
>>> pd.eval("double_age = df.age * 2", target=df)
  animal  age  double_age
0    dog   10          20
1    pig   20          40
```

3.2.7 Hashing

util.hash_array(vals[, encoding, hash_key, ...])	Given a 1d array, return an array of deterministic integers.
util.hash_pandas_object(obj[, index, ...])	Return a data hash of the Index/Series/DataFrame.

pandas.util.hash_array

pandas.util.**hash_array**(*vals*, *encoding='utf8'*, *hash_key='0123456789123456'*, *categorize=True*)

Given a 1d array, return an array of deterministic integers.

Parameters

vals [ndarray, Categorical]

encoding [str, default 'utf8'] Encoding for data & key when strings.

hash_key [str, default _default_hash_key] Hash_key for string key to encode.

categorize [bool, default True] Whether to first categorize object arrays before hashing. This is more efficient when the array contains duplicate values.

Returns

1d uint64 numpy array of hash values, same length as the vals

pandas.util.hash_pandas_object

pandas.util.**hash_pandas_object**(*obj*, *index=True*, *encoding='utf8'*, *hash_key='0123456789123456'*, *categorize=True*)

Return a data hash of the Index/Series/DataFrame.

Parameters

index [bool, default True] Include the index in the hash (if Series/DataFrame).

encoding [str, default 'utf8'] Encoding for data & key when strings.

hash_key [str, default _default_hash_key] Hash_key for string key to encode.

categorize [bool, default True] Whether to first categorize object arrays before hashing. This is more efficient when the array contains duplicate values.

Returns

Series of uint64, same length as the object

3.2.8 Testing

test([extra_args])	

pandas.test

pandas.**test**(*extra_args=None*)

3.3 Series

3.3.1 Constructor

Series([data, index, dtype, name, copy, ...])	One-dimensional ndarray with axis labels (including time series).

pandas.Series

class pandas.**Series**(*data=None*, *index=None*, *dtype=None*, *name=None*, *copy=False*, *fastpath=False*)

One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be a hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical methods from ndarray have been overridden to automatically exclude missing data (currently represented as NaN).

Operations between Series (+, -, /, , *) align values based on their associated index values– they need not be the same length. The result index will be the sorted union of the two indexes.

Parameters

data [array-like, Iterable, dict, or scalar value] Contains data stored in Series. If data is a dict, argument order is maintained.

index [array-like or Index (1d)] Values must be hashable and have the same length as *data*. Non-unique index values are allowed. Will default to RangeIndex (0, 1, 2, …, n) if not provided. If data is dict-like and index is None, then the keys in the data are used as the index. If the index is not None, the resulting Series is reindexed with the index values.

dtype [str, numpy.dtype, or ExtensionDtype, optional] Data type for the output Series. If not specified, this will be inferred from *data*. See the *user guide* for more usages.

name [str, optional] The name to give to the Series.

copy [bool, default False] Copy input data.

Examples

Constructing Series from a dictionary with an Index specified

```
>>> d = {'a': 1, 'b': 2, 'c': 3}
>>> ser = pd.Series(data=d, index=['a', 'b', 'c'])
>>> ser
a   1
b   2
c   3
dtype: int64
```

The keys of the dictionary match with the Index values, hence the Index values have no effect.

```
>>> d = {'a': 1, 'b': 2, 'c': 3}
>>> ser = pd.Series(data=d, index=['x', 'y', 'z'])
>>> ser
x   NaN
y   NaN
z   NaN
dtype: float64
```

Note that the Index is first build with the keys from the dictionary. After this the Series is reindexed with the given Index values, hence we get all NaN as a result.

Attributes

T	Return the transpose, which is by definition self.
array	The ExtensionArray of the data backing this Series or Index.
at	Access a single value for a row/column label pair.
attrs	Dictionary of global attributes of this dataset.
axes	Return a list of the row axis labels.
dtype	Return the dtype object of the underlying data.
dtypes	Return the dtype object of the underlying data.
flags	Get the properties associated with this pandas object.
hasnans	Return if I have any nans; enables various perf speedups.
iat	Access a single value for a row/column pair by integer position.
iloc	Purely integer-location based indexing for selection by position.

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index	The index (axis labels) of the Series.
is_monotonic	Return boolean if values in the object are monotonic_increasing.
is_monotonic_decreasing	Return boolean if values in the object are monotonic_decreasing.
is_monotonic_increasing	Alias for is_monotonic.
is_unique	Return boolean if values in the object are unique.
loc	Access a group of rows and columns by label(s) or a boolean array.
name	Return the name of the Series.
nbytes	Return the number of bytes in the underlying data.
ndim	Number of dimensions of the underlying data, by definition 1.
shape	Return a tuple of the shape of the underlying data.
size	Return the number of elements in the underlying data.
values	Return Series as ndarray or ndarray-like depending on the dtype.

pandas.Series.T

property Series.**T**

Return the transpose, which is by definition self.

pandas.Series.array

property Series.**array**

The ExtensionArray of the data backing this Series or Index.

New in version 0.24.0.

Returns

ExtensionArray An ExtensionArray of the values stored within. For extension types, this is the actual array. For NumPy native types, this is a thin (no copy) wrapper around `numpy.ndarray`.

`.array` differs `.values` which may require converting the data to a different form.

See also:

Index.to_numpy Similar method that always returns a NumPy array.

Series.to_numpy Similar method that always returns a NumPy array.

Notes

This table lays out the different array types for each extension dtype within pandas.

dtype	array type
category	Categorical
period	PeriodArray
interval	IntervalArray
IntegerNA	IntegerArray
string	StringArray
boolean	BooleanArray
datetime64[ns, tz]	DatetimeArray

For any 3rd-party extension types, the array type will be an ExtensionArray.

For all remaining dtypes `.array` will be a `arrays.NumpyExtensionArray` wrapping the actual ndarray stored within. If you absolutely need a NumPy array (possibly with copying / coercing data), then use *`Series.to_numpy()`* instead.

Examples

For regular NumPy types like int, and float, a PandasArray is returned.

```
>>> pd.Series([1, 2, 3]).array
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
```

For extension types, like Categorical, the actual ExtensionArray is returned

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.array
['a', 'b', 'a']
Categories (2, object): ['a', 'b']
```

pandas.Series.at

property Series.**at**

Access a single value for a row/column label pair.

Similar to `loc`, in that both provide label-based lookups. Use `at` if you only need to get or set a single value in a DataFrame or Series.

Raises

KeyError If 'label' does not exist in DataFrame.

See also:

DataFrame.iat Access a single value for a row/column pair by integer position.

DataFrame.loc Access a group of rows and columns by label(s).

Series.at Access a single value using a label.

Examples

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                   index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
    A   B   C
4   0   2   3
5   0   4   1
6  10  20  30
```

Get value at specified row/column pair

```
>>> df.at[4, 'B']
2
```

Set value at specified row/column pair

```
>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```

Get value within a Series

```
>>> df.loc[5].at['B']
4
```

pandas.Series.attrs

property Series.**attrs**

Dictionary of global attributes of this dataset.

> **Warning:** attrs is experimental and may change without warning.

See also:

DataFrame.flags Global flags applying to this object.

pandas.Series.axes

property Series.**axes**

Return a list of the row axis labels.

pandas.Series.dtype

property Series.**dtype**
Return the dtype object of the underlying data.

pandas.Series.dtypes

property Series.**dtypes**
Return the dtype object of the underlying data.

pandas.Series.flags

property Series.**flags**
Get the properties associated with this pandas object.

The available flags are

- *Flags.allows_duplicate_labels*

See also:

Flags Flags that apply to pandas objects.

DataFrame.attrs Global metadata applying to this dataset.

Notes

"Flags" differ from "metadata". Flags reflect properties of the pandas object (the Series or DataFrame). Metadata refer to properties of the dataset, and should be stored in *DataFrame.attrs*.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2]})
>>> df.flags
<Flags(allows_duplicate_labels=True)>
```

Flags can be get or set using `.`

```
>>> df.flags.allows_duplicate_labels
True
>>> df.flags.allows_duplicate_labels = False
```

Or by slicing with a key

```
>>> df.flags["allows_duplicate_labels"]
False
>>> df.flags["allows_duplicate_labels"] = True
```

pandas.Series.hasnans

property Series.**hasnans**
Return if I have any nans; enables various perf speedups.

pandas.Series.iat

property Series.**iat**
Access a single value for a row/column pair by integer position.

Similar to `iloc`, in that both provide integer-based lookups. Use `iat` if you only need to get or set a single value in a DataFrame or Series.

Raises

IndexError When integer position is out of bounds.

See also:

DataFrame.at Access a single value for a row/column label pair.

DataFrame.loc Access a group of rows and columns by label(s).

DataFrame.iloc Access a group of rows and columns by integer position(s).

Examples

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                   columns=['A', 'B', 'C'])
>>> df
    A   B   C
0   0   2   3
1   0   4   1
2  10  20  30
```

Get value at specified row/column pair

```
>>> df.iat[1, 2]
1
```

Set value at specified row/column pair

```
>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
```

Get value within a series

```
>>> df.loc[0].iat[1]
2
```

pandas.Series.iloc

property Series.**iloc**

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.
- A `callable` function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above). This is useful in method chains, when you don't have a reference to the calling object, but would like to base your selection on some value.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*.

See also:

DataFrame.iat Fast integer location scalar accessor.

DataFrame.loc Purely label-location based indexer for selection by label.

Series.iloc Purely integer-location based indexing for selection by position.

Examples

```
>>> mydict = [{'a': 1, 'b': 2, 'c': 3, 'd': 4},
...           {'a': 100, 'b': 200, 'c': 300, 'd': 400},
...           {'a': 1000, 'b': 2000, 'c': 3000, 'd': 4000 }]
>>> df = pd.DataFrame(mydict)
>>> df
      a     b     c     d
0     1     2     3     4
1   100   200   300   400
2  1000  2000  3000  4000
```

Indexing just the rows

With a scalar integer.

```
>>> type(df.iloc[0])
<class 'pandas.core.series.Series'>
>>> df.iloc[0]
a    1
b    2
c    3
d    4
Name: 0, dtype: int64
```

With a list of integers.

```
>>> df.iloc[[0]]
   a  b  c  d
0  1  2  3  4
>>> type(df.iloc[[0]])
<class 'pandas.core.frame.DataFrame'>
```

```
>>> df.iloc[[0, 1]]
     a    b    c    d
0    1    2    3    4
1  100  200  300  400
```

With a *slice* object.

```
>>> df.iloc[:3]
      a     b     c     d
0     1     2     3     4
1   100   200   300   400
2  1000  2000  3000  4000
```

With a boolean mask the same length as the index.

```
>>> df.iloc[[True, False, True]]
      a     b     c     d
0     1     2     3     4
2  1000  2000  3000  4000
```

With a callable, useful in method chains. The *x* passed to the `lambda` is the DataFrame being sliced. This selects the rows whose index label even.

```
>>> df.iloc[lambda x: x.index % 2 == 0]
      a     b     c     d
0     1     2     3     4
2  1000  2000  3000  4000
```

Indexing both axes

You can mix the indexer types for the index and columns. Use `:` to select the entire axis.

With scalar integers.

```
>>> df.iloc[0, 1]
2
```

With lists of integers.

```
>>> df.iloc[[0, 2], [1, 3]]
      b     d
0     2     4
2  2000  4000
```

With *slice* objects.

```
>>> df.iloc[1:3, 0:3]
      a     b     c
1   100   200   300
2  1000  2000  3000
```

With a boolean array whose length matches the columns.

```
>>> df.iloc[:, [True, False, True, False]]
      a     c
0     1     3
1   100   300
2  1000  3000
```

With a callable function that expects the Series or DataFrame.

```
>>> df.iloc[:, lambda df: [0, 2]]
      a     c
0     1     3
1   100   300
2  1000  3000
```

pandas.Series.index

Series.**index**: *Index*
The index (axis labels) of the Series.

pandas.Series.is_monotonic

property Series.**is_monotonic**
Return boolean if values in the object are monotonic_increasing.

Returns

bool

pandas.Series.is_monotonic_decreasing

property Series.**is_monotonic_decreasing**
Return boolean if values in the object are monotonic_decreasing.

Returns

bool

pandas.Series.is_monotonic_increasing

property Series.**is_monotonic_increasing**
Alias for is_monotonic.

pandas.Series.is_unique

property Series.**is_unique**

Return boolean if values in the object are unique.

Returns

bool

pandas.Series.loc

property Series.**loc**

Access a group of rows and columns by label(s) or a boolean array.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'`.

> **Warning:** Note that contrary to usual python slices, **both** the start and the stop are included

- A boolean array of the same length as the axis being sliced, e.g. `[True, False, True]`.
- An alignable boolean Series. The index of the key will be aligned before masking.
- An alignable Index. The Index of the returned selection will be the input.
- A `callable` function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above)

See more at *Selection by Label*.

Raises

KeyError If any items are not found.

IndexingError If an indexed key is passed and its index is unalignable to the frame index.

See also:

DataFrame.at Access a single value for a row/column label pair.

DataFrame.iloc Access group of rows and columns by integer position(s).

DataFrame.xs Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

Series.loc Access group of values using labels.

Examples

Getting values

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...       index=['cobra', 'viper', 'sidewinder'],
...       columns=['max_speed', 'shield'])
>>> df
            max_speed  shield
cobra               1       2
viper               4       5
sidewinder          7       8
```

Single label. Note this returns the row as a Series.

```
>>> df.loc['viper']
max_speed    4
shield       5
Name: viper, dtype: int64
```

List of labels. Note using `[[]]` returns a DataFrame.

```
>>> df.loc[['viper', 'sidewinder']]
            max_speed  shield
viper               4       5
sidewinder          7       8
```

Single label for row and column

```
>>> df.loc['cobra', 'shield']
2
```

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc['cobra':'viper', 'max_speed']
cobra    1
viper    4
Name: max_speed, dtype: int64
```

Boolean list with the same length as the row axis

```
>>> df.loc[[False, False, True]]
            max_speed  shield
sidewinder          7       8
```

Alignable boolean Series:

```
>>> df.loc[pd.Series([False, True, False],
...        index=['viper', 'sidewinder', 'cobra'])]
            max_speed  shield
sidewinder          7       8
```

Index (same behavior as `df.reindex`)

```
>>> df.loc[pd.Index(["cobra", "viper"], name="foo")]
       max_speed  shield
```

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```
foo
cobra          1       2
viper          4       5
```

Conditional that returns a boolean Series

```
>>> df.loc[df['shield'] > 6]
            max_speed  shield
sidewinder          7       8
```

Conditional that returns a boolean Series with column labels specified

```
>>> df.loc[df['shield'] > 6, ['max_speed']]
            max_speed
sidewinder          7
```

Callable that returns a boolean Series

```
>>> df.loc[lambda df: df['shield'] == 8]
            max_speed  shield
sidewinder          7       8
```

Setting values

Set value for all items matching the list of labels

```
>>> df.loc[['viper', 'sidewinder'], ['shield']] = 50
>>> df
            max_speed  shield
cobra               1       2
viper               4      50
sidewinder          7      50
```

Set value for an entire row

```
>>> df.loc['cobra'] = 10
>>> df
            max_speed  shield
cobra              10      10
viper               4      50
sidewinder          7      50
```

Set value for an entire column

```
>>> df.loc[:, 'max_speed'] = 30
>>> df
            max_speed  shield
cobra              30      10
viper              30      50
sidewinder         30      50
```

Set value for rows matching callable condition

```
>>> df.loc[df['shield'] > 35] = 0
>>> df
            max_speed  shield
cobra              30      10
```

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```
viper               0       0
sidewinder          0       0
```

Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...       index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
   max_speed  shield
7          1       2
8          4       5
9          7       8
```

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc[7:9]
   max_speed  shield
7          1       2
8          4       5
9          7       8
```

Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

```
>>> tuples = [
...     ('cobra', 'mark i'), ('cobra', 'mark ii'),
...     ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
...     ('viper', 'mark ii'), ('viper', 'mark iii')
... ]
>>> index = pd.MultiIndex.from_tuples(tuples)
>>> values = [[12, 2], [0, 4], [10, 20],
...           [1, 4], [7, 1], [16, 36]]
>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
                     max_speed  shield
cobra      mark i           12       2
           mark ii           0       4
sidewinder mark i           10      20
           mark ii           1       4
viper      mark ii           7       1
           mark iii         16      36
```

Single label. Note this returns a DataFrame with a single index.

```
>>> df.loc['cobra']
         max_speed  shield
mark i          12       2
mark ii          0       4
```

Single index tuple. Note this returns a Series.

```
>>> df.loc[('cobra', 'mark ii')]
max_speed    0
```

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```
shield       4
Name: (cobra, mark ii), dtype: int64
```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```
>>> df.loc['cobra', 'mark i']
max_speed    12
shield        2
Name: (cobra, mark i), dtype: int64
```

Single tuple. Note using `[[]]` returns a DataFrame.

```
>>> df.loc[[('cobra', 'mark ii')]]
               max_speed  shield
cobra mark ii          0       4
```

Single tuple for the index with a single label for the column

```
>>> df.loc[('cobra', 'mark i'), 'shield']
2
```

Slice from index tuple to single label

```
>>> df.loc[('cobra', 'mark i'):'viper']
                     max_speed  shield
cobra      mark i           12       2
           mark ii           0       4
sidewinder mark i           10      20
           mark ii           1       4
viper      mark ii           7       1
           mark iii         16      36
```

Slice from index tuple to index tuple

```
>>> df.loc[('cobra', 'mark i'):('viper', 'mark ii')]
                    max_speed  shield
cobra      mark i          12       2
           mark ii          0       4
sidewinder mark i          10      20
           mark ii          1       4
viper      mark ii          7       1
```

pandas.Series.name

property Series.**name**

Return the name of the Series.

The name of a Series becomes its index or column name if it is used to form a DataFrame. It is also used whenever displaying the Series using the interpreter.

Returns

label (hashable object) The name of the Series, also the column name if part of a DataFrame.

See also:

Series.rename Sets the Series name when given a scalar input.

Index.name Corresponding Index property.

Examples

The Series name can be set initially when calling the constructor.

```
>>> s = pd.Series([1, 2, 3], dtype=np.int64, name='Numbers')
>>> s
0    1
1    2
2    3
Name: Numbers, dtype: int64
>>> s.name = "Integers"
>>> s
0    1
1    2
2    3
Name: Integers, dtype: int64
```

The name of a Series within a DataFrame is its column name.

```
>>> df = pd.DataFrame([[1, 2], [3, 4], [5, 6]],
...                   columns=["Odd Numbers", "Even Numbers"])
>>> df
   Odd Numbers  Even Numbers
0            1             2
1            3             4
2            5             6
>>> df["Even Numbers"].name
'Even Numbers'
```

pandas.Series.nbytes

property Series.**nbytes**
Return the number of bytes in the underlying data.

pandas.Series.ndim

property Series.**ndim**
Number of dimensions of the underlying data, by definition 1.

pandas.Series.shape

property Series.**shape**
Return a tuple of the shape of the underlying data.

pandas.Series.size

property Series.**size**
Return the number of elements in the underlying data.

pandas.Series.values

property Series.**values**
Return Series as ndarray or ndarray-like depending on the dtype.

> **Warning:** We recommend using *Series.array* or *Series.to_numpy()*, depending on whether you need a reference to the underlying data or a NumPy array.

Returns

numpy.ndarray or ndarray-like

See also:

Series.array Reference to the underlying data.

Series.to_numpy A NumPy array representing the underlying data.

Examples

```
>>> pd.Series([1, 2, 3]).values
array([1, 2, 3])
```

```
>>> pd.Series(list('aabc')).values
array(['a', 'a', 'b', 'c'], dtype=object)
```

```
>>> pd.Series(list('aabc')).astype('category').values
['a', 'a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Timezone aware datetime data is converted to UTC:

```
>>> pd.Series(pd.date_range('20130101', periods=3,
...                         tz='US/Eastern')).values
array(['2013-01-01T05:00:00.000000000',
       '2013-01-02T05:00:00.000000000',
       '2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

empty	

Methods

abs()	Return a Series/DataFrame with absolute numeric value of each element.
add(other[, level, fill_value, axis])	Return Addition of series and other, element-wise (binary operator *add*).
add_prefix(prefix)	Prefix labels with string *prefix*.
add_suffix(suffix)	Suffix labels with string *suffix*.
agg([func, axis])	Aggregate using one or more operations over the specified axis.
aggregate([func, axis])	Aggregate using one or more operations over the specified axis.
align(other[, join, axis, level, copy, ...])	Align two objects on their axes with the specified join method.
all([axis, bool_only, skipna, level])	Return whether all elements are True, potentially over an axis.
any([axis, bool_only, skipna, level])	Return whether any element is True, potentially over an axis.
append(to_append[, ignore_index, ...])	Concatenate two or more Series.
apply(func[, convert_dtype, args])	Invoke function on values of Series.
argmax([axis, skipna])	Return int position of the largest value in the Series.
argmin([axis, skipna])	Return int position of the smallest value in the Series.
argsort([axis, kind, order])	Return the integer indices that would sort the Series values.
asfreq(freq[, method, how, normalize, ...])	Convert TimeSeries to specified frequency.
asof(where[, subset])	Return the last row(s) without any NaNs before *where*.
astype(dtype[, copy, errors])	Cast a pandas object to a specified dtype `dtype`.
at_time(time[, asof, axis])	Select values at particular time of day (e.g., 9:30AM).
autocorr([lag])	Compute the lag-N autocorrelation.
backfill([axis, inplace, limit, downcast])	Synonym for *DataFrame.fillna()* with `method='bfill'`.
between(left, right[, inclusive])	Return boolean Series equivalent to left <= series <= right.
between_time(start_time, end_time[, ...])	Select values between particular times of the day (e.g., 9:00-9:30 AM).
bfill([axis, inplace, limit, downcast])	Synonym for *DataFrame.fillna()* with `method='bfill'`.
bool()	Return the bool of a single element Series or DataFrame.
cat	alias of `pandas.core.arrays.categorical.CategoricalAccessor`
clip([lower, upper, axis, inplace])	Trim values at input threshold(s).
combine(other, func[, fill_value])	Combine the Series with a Series or scalar according to *func*.
combine_first(other)	Combine Series values, choosing the calling Series's values first.
compare(other[, align_axis, keep_shape, ...])	Compare to another Series and show the differences.
convert_dtypes([infer_objects, ...])	Convert columns to best possible dtypes using dtypes supporting `pd.NA`.

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copy([deep])	Make a copy of this object's indices and data.
corr(other[, method, min_periods])	Compute correlation with *other* Series, excluding missing values.
count([level])	Return number of non-NA/null observations in the Series.
cov(other[, min_periods, ddof])	Compute covariance with Series, excluding missing values.
cummax([axis, skipna])	Return cumulative maximum over a DataFrame or Series axis.
cummin([axis, skipna])	Return cumulative minimum over a DataFrame or Series axis.
cumprod([axis, skipna])	Return cumulative product over a DataFrame or Series axis.
cumsum([axis, skipna])	Return cumulative sum over a DataFrame or Series axis.
describe([percentiles, include, exclude, ...])	Generate descriptive statistics.
diff([periods])	First discrete difference of element.
div(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *truediv*).
divide(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *truediv*).
divmod(other[, level, fill_value, axis])	Return Integer division and modulo of series and other, element-wise (binary operator *divmod*).
dot(other)	Compute the dot product between the Series and the columns of other.
drop([labels, axis, index, columns, level, ...])	Return Series with specified index labels removed.
drop_duplicates([keep, inplace])	Return Series with duplicate values removed.
droplevel(level[, axis])	Return DataFrame with requested index / column level(s) removed.
dropna([axis, inplace, how])	Return a new Series with missing values removed.
dt	alias of pandas.core.indexes.accessors.CombinedDatetimelikeProperties
duplicated([keep])	Indicate duplicate Series values.
eq(other[, level, fill_value, axis])	Return Equal to of series and other, element-wise (binary operator *eq*).
equals(other)	Test whether two objects contain the same elements.
ewm([com, span, halflife, alpha, ...])	Provide exponential weighted (EW) functions.
expanding([min_periods, center, axis])	Provide expanding transformations.
explode([ignore_index])	Transform each element of a list-like to a row.
factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable.
ffill([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='ffill'.
fillna([value, method, axis, inplace, ...])	Fill NA/NaN values using the specified method.
filter([items, like, regex, axis])	Subset the dataframe rows or columns according to the specified index labels.
first(offset)	Select initial periods of time series data based on a date offset.
first_valid_index()	Return index for first non-NA/null value.

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floordiv(other[, level, fill_value, axis])	Return Integer division of series and other, element-wise (binary operator *floordiv*).
ge(other[, level, fill_value, axis])	Return Greater than or equal to of series and other, element-wise (binary operator *ge*).
get(key[, default])	Get item from object for given key (ex: DataFrame column).
groupby([by, axis, level, as_index, sort, ...])	Group Series using a mapper or by a Series of columns.
gt(other[, level, fill_value, axis])	Return Greater than of series and other, element-wise (binary operator *gt*).
head([n])	Return the first *n* rows.
hist([by, ax, grid, xlabelsize, xrot, ...])	Draw histogram of the input series using matplotlib.
idxmax([axis, skipna])	Return the row label of the maximum value.
idxmin([axis, skipna])	Return the row label of the minimum value.
infer_objects()	Attempt to infer better dtypes for object columns.
interpolate([method, axis, limit, inplace, ...])	Fill NaN values using an interpolation method.
isin(values)	Whether elements in Series are contained in *values*.
isna()	Detect missing values.
isnull()	Detect missing values.
item()	Return the first element of the underlying data as a Python scalar.
items()	Lazily iterate over (index, value) tuples.
iteritems()	Lazily iterate over (index, value) tuples.
keys()	Return alias for index.
kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis.
kurtosis([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis.
last(offset)	Select final periods of time series data based on a date offset.
last_valid_index()	Return index for last non-NA/null value.
le(other[, level, fill_value, axis])	Return Less than or equal to of series and other, element-wise (binary operator *le*).
lt(other[, level, fill_value, axis])	Return Less than of series and other, element-wise (binary operator *lt*).
mad([axis, skipna, level])	Return the mean absolute deviation of the values over the requested axis.
map(arg[, na_action])	Map values of Series according to input correspondence.
mask(cond[, other, inplace, axis, level, ...])	Replace values where the condition is True.
max([axis, skipna, level, numeric_only])	Return the maximum of the values over the requested axis.
mean([axis, skipna, level, numeric_only])	Return the mean of the values over the requested axis.
median([axis, skipna, level, numeric_only])	Return the median of the values over the requested axis.
memory_usage([index, deep])	Return the memory usage of the Series.
min([axis, skipna, level, numeric_only])	Return the minimum of the values over the requested axis.
mod(other[, level, fill_value, axis])	Return Modulo of series and other, element-wise (binary operator *mod*).
mode([dropna])	Return the mode(s) of the Series.

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mul(other[, level, fill_value, axis])	Return Multiplication of series and other, element-wise (binary operator *mul*).
multiply(other[, level, fill_value, axis])	Return Multiplication of series and other, element-wise (binary operator *mul*).
ne(other[, level, fill_value, axis])	Return Not equal to of series and other, element-wise (binary operator *ne*).
nlargest([n, keep])	Return the largest *n* elements.
notna()	Detect existing (non-missing) values.
notnull()	Detect existing (non-missing) values.
nsmallest([n, keep])	Return the smallest *n* elements.
nunique([dropna])	Return number of unique elements in the object.
pad([axis, inplace, limit, downcast])	Synonym for *DataFrame.fillna()* with `method='ffill'`.
pct_change([periods, fill_method, limit, freq])	Percentage change between the current and a prior element.
pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs).
plot	alias of `pandas.plotting._core.PlotAccessor`
pop(item)	Return item and drops from series.
pow(other[, level, fill_value, axis])	Return Exponential power of series and other, element-wise (binary operator *pow*).
prod([axis, skipna, level, numeric_only, ...])	Return the product of the values over the requested axis.
product([axis, skipna, level, numeric_only, ...])	Return the product of the values over the requested axis.
quantile([q, interpolation])	Return value at the given quantile.
radd(other[, level, fill_value, axis])	Return Addition of series and other, element-wise (binary operator *radd*).
rank([axis, method, numeric_only, ...])	Compute numerical data ranks (1 through n) along axis.
ravel([order])	Return the flattened underlying data as an ndarray.
rdiv(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *rtruediv*).
rdivmod(other[, level, fill_value, axis])	Return Integer division and modulo of series and other, element-wise (binary operator *rdivmod*).
reindex([index])	Conform Series to new index with optional filling logic.
reindex_like(other[, method, copy, limit, ...])	Return an object with matching indices as other object.
rename([index, axis, copy, inplace, level, ...])	Alter Series index labels or name.
rename_axis([mapper, index, columns, axis, ...])	Set the name of the axis for the index or columns.
reorder_levels(order)	Rearrange index levels using input order.
repeat(repeats[, axis])	Repeat elements of a Series.
replace([to_replace, value, inplace, limit, ...])	Replace values given in *to_replace* with *value*.
resample(rule[, axis, closed, label, ...])	Resample time-series data.
reset_index([level, drop, name, inplace])	Generate a new DataFrame or Series with the index reset.
rfloordiv(other[, level, fill_value, axis])	Return Integer division of series and other, element-wise (binary operator *rfloordiv*).

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rmod(other[, level, fill_value, axis])	Return Modulo of series and other, element-wise (binary operator *rmod*).
rmul(other[, level, fill_value, axis])	Return Multiplication of series and other, element-wise (binary operator *rmul*).
rolling(window[, min_periods, center, ...])	Provide rolling window calculations.
round([decimals])	Round each value in a Series to the given number of decimals.
rpow(other[, level, fill_value, axis])	Return Exponential power of series and other, element-wise (binary operator *rpow*).
rsub(other[, level, fill_value, axis])	Return Subtraction of series and other, element-wise (binary operator *rsub*).
rtruediv(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *rtruediv*).
sample([n, frac, replace, weights, ...])	Return a random sample of items from an axis of object.
searchsorted(value[, side, sorter])	Find indices where elements should be inserted to maintain order.
sem([axis, skipna, level, ddof, numeric_only])	Return unbiased standard error of the mean over requested axis.
set_axis(labels[, axis, inplace])	Assign desired index to given axis.
set_flags(*[, copy, allows_duplicate_labels])	Return a new object with updated flags.
shift([periods, freq, axis, fill_value])	Shift index by desired number of periods with an optional time *freq*.
skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis.
slice_shift([periods, axis])	(DEPRECATED) Equivalent to *shift* without copying data.
sort_index([axis, level, ascending, ...])	Sort Series by index labels.
sort_values([axis, ascending, inplace, ...])	Sort by the values.
sparse	alias of `pandas.core.arrays.sparse.accessor.SparseAccessor`
squeeze([axis])	Squeeze 1 dimensional axis objects into scalars.
std([axis, skipna, level, ddof, numeric_only])	Return sample standard deviation over requested axis.
str	alias of `pandas.core.strings.accessor.StringMethods`
sub(other[, level, fill_value, axis])	Return Subtraction of series and other, element-wise (binary operator *sub*).
subtract(other[, level, fill_value, axis])	Return Subtraction of series and other, element-wise (binary operator *sub*).
sum([axis, skipna, level, numeric_only, ...])	Return the sum of the values over the requested axis.
swapaxes(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately.
swaplevel([i, j, copy])	Swap levels i and j in a *MultiIndex*.
tail([n])	Return the last *n* rows.
take(indices[, axis, is_copy])	Return the elements in the given *positional* indices along an axis.
to_clipboard([excel, sep])	Copy object to the system clipboard.
to_csv([path_or_buf, sep, na_rep, ...])	Write object to a comma-separated values (csv) file.
to_dict([into])	Convert Series to {label -> value} dict or dict-like object.
to_excel(excel_writer[, sheet_name, na_rep, ...])	Write object to an Excel sheet.

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to_frame([name])	Convert Series to DataFrame.
to_hdf(path_or_buf, key[, mode, complevel, ...])	Write the contained data to an HDF5 file using HDFStore.
to_json([path_or_buf, orient, date_format, ...])	Convert the object to a JSON string.
to_latex([buf, columns, col_space, header, ...])	Render object to a LaTeX tabular, longtable, or nested table/tabular.
to_list()	Return a list of the values.
to_markdown([buf, mode, index, storage_options])	Print Series in Markdown-friendly format.
to_numpy([dtype, copy, na_value])	A NumPy ndarray representing the values in this Series or Index.
to_period([freq, copy])	Convert Series from DatetimeIndex to PeriodIndex.
to_pickle(path[, compression, protocol, ...])	Pickle (serialize) object to file.
to_sql(name, con[, schema, if_exists, ...])	Write records stored in a DataFrame to a SQL database.
to_string([buf, na_rep, float_format, ...])	Render a string representation of the Series.
to_timestamp([freq, how, copy])	Cast to DatetimeIndex of Timestamps, at *beginning* of period.
to_xarray()	Return an xarray object from the pandas object.
tolist()	Return a list of the values.
transform(func[, axis])	Call `func` on self producing a Series with transformed values.
transpose(*args, **kwargs)	Return the transpose, which is by definition self.
truediv(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *truediv*).
truncate([before, after, axis, copy])	Truncate a Series or DataFrame before and after some index value.
tshift([periods, freq, axis])	(DEPRECATED) Shift the time index, using the index's frequency if available.
tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
tz_localize(tz[, axis, level, copy, ...])	Localize tz-naive index of a Series or DataFrame to target time zone.
unique()	Return unique values of Series object.
unstack([level, fill_value])	Unstack, also known as pivot, Series with MultiIndex to produce DataFrame.
update(other)	Modify Series in place using values from passed Series.
value_counts([normalize, sort, ascending, ...])	Return a Series containing counts of unique values.
var([axis, skipna, level, ddof, numeric_only])	Return unbiased variance over requested axis.
view([dtype])	Create a new view of the Series.
where(cond[, other, inplace, axis, level, ...])	Replace values where the condition is False.
xs(key[, axis, level, drop_level])	Return cross-section from the Series/DataFrame.

pandas.Series.abs

Series.**abs**()

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

Returns

abs Series/DataFrame containing the absolute value of each element.

See also:

numpy.absolute Calculate the absolute value element-wise.

Notes

For `complex` inputs, `1.2 + 1j`, the absolute value is $\sqrt{a^2 + b^2}$.

Examples

Absolute numeric values in a Series.

```
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0    1.10
1    2.00
2    3.33
3    4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.

```
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0    1.56205
dtype: float64
```

Absolute numeric values in a Series with a Timedelta element.

```
>>> s = pd.Series([pd.Timedelta('1 days')])
>>> s.abs()
0   1 days
dtype: timedelta64[ns]
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```
>>> df = pd.DataFrame({
...     'a': [4, 5, 6, 7],
...     'b': [10, 20, 30, 40],
...     'c': [100, 50, -30, -50]
... })
>>> df
     a    b    c
0    4   10  100
1    5   20   50
```

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```
2    6   30  -30
3    7   40  -50
>>> df.loc[(df.c - 43).abs().argsort()]
     a    b    c
1    5   20   50
0    4   10  100
2    6   30  -30
3    7   40  -50
```

pandas.Series.add

Series.**add**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Addition of series and other, element-wise (binary operator *add*).

Equivalent to `series + other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.radd Reverse of the Addition operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
```

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```
b    1.0
c    1.0
d    1.0
e    NaN
dtype: float64
```

pandas.Series.add_prefix

Series.**add_prefix**(*prefix*)

Prefix labels with string *prefix*.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

Parameters

prefix [str] The string to add before each label.

Returns

Series or DataFrame New Series or DataFrame with updated labels.

See also:

Series.add_suffix Suffix row labels with string *suffix*.

DataFrame.add_suffix Suffix column labels with string *suffix*.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_prefix('item_')
item_0    1
item_1    2
item_2    3
item_3    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```
>>> df.add_prefix('col_')
     col_A  col_B
```

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```
0       1       3
1       2       4
2       3       5
3       4       6
```

pandas.Series.add_suffix

Series.**add_suffix**(*suffix*)

Suffix labels with string *suffix*.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

Parameters

suffix [str] The string to add after each label.

Returns

Series or DataFrame New Series or DataFrame with updated labels.

See also:

Series.add_prefix Prefix row labels with string *prefix*.

DataFrame.add_prefix Prefix column labels with string *prefix*.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_suffix('_item')
0_item    1
1_item    2
2_item    3
3_item    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```
>>> df.add_suffix('_col')
     A_col  B_col
0       1       3
```

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```
1       2       4
2       3       5
3       4       6
```

pandas.Series.agg

Series.**agg**(*func=None*, *axis=0*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

axis [{0 or 'index'}] Parameter needed for compatibility with DataFrame.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

Series.apply Invoke function on a Series.

Series.transform Transform function producing a Series with like indexes.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.agg('min')
1
```

```
>>> s.agg(['min', 'max'])
min   1
max   4
dtype: int64
```

pandas.Series.aggregate

`Series.`**`aggregate`**(*func=None*, *axis=0*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

axis [{0 or 'index'}] Parameter needed for compatibility with DataFrame.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

Series.apply Invoke function on a Series.

Series.transform Transform function producing a Series with like indexes.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.agg('min')
1
```

```
>>> s.agg(['min', 'max'])
min   1
max   4
dtype: int64
```

pandas.Series.align

Series.**align**(*other*, *join='outer'*, *axis=None*, *level=None*, *copy=True*, *fill_value=None*, *method=None*, *limit=None*, *fill_axis=0*, *broadcast_axis=None*)

Align two objects on their axes with the specified join method.

Join method is specified for each axis Index.

Parameters

other [DataFrame or Series]

join [{'outer', 'inner', 'left', 'right'}, default 'outer']

axis [allowed axis of the other object, default None] Align on index (0), columns (1), or both (None).

level [int or level name, default None] Broadcast across a level, matching Index values on the passed MultiIndex level.

copy [bool, default True] Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any "compatible" value.

method [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series:

- pad / ffill: propagate last valid observation forward to next valid.
- backfill / bfill: use NEXT valid observation to fill gap.

limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

fill_axis [{0 or 'index'}, default 0] Filling axis, method and limit.

broadcast_axis [{0 or 'index'}, default None] Broadcast values along this axis, if aligning two objects of different dimensions.

Returns

(left, right) [(Series, type of other)] Aligned objects.

pandas.Series.all

`Series.`**`all`**(*axis=0*, *bool_only=None*, *skipna=True*, *level=None*, ***kwargs*)

Return whether all elements are True, potentially over an axis.

Returns True unless there at least one element within a series or along a Dataframe axis that is False or equivalent (e.g. zero or empty).

Parameters

axis [{0 or 'index', 1 or 'columns', None}, default 0] Indicate which axis or axes should be reduced.

- 0 / 'index' : reduce the index, return a Series whose index is the original column labels.
- 1 / 'columns' : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be True, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

****kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series If level is specified, then, Series is returned; otherwise, scalar is returned.

See also:

Series.all Return True if all elements are True.

DataFrame.any Return True if one (or more) elements are True.

Examples

Series

```
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
>>> pd.Series([]).all()
True
>>> pd.Series([np.nan]).all()
True
>>> pd.Series([np.nan]).all(skipna=False)
True
```

DataFrames

Create a dataframe from a dictionary.

```
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
   col1   col2
0  True   True
1  True  False
```

Default behaviour checks if column-wise values all return True.

```
>>> df.all()
col1     True
col2    False
dtype: bool
```

Specify `axis='columns'` to check if row-wise values all return True.

```
>>> df.all(axis='columns')
0     True
1    False
dtype: bool
```

Or `axis=None` for whether every value is True.

```
>>> df.all(axis=None)
False
```

pandas.Series.any

`Series.`**`any`**(*axis=0*, *bool_only=None*, *skipna=True*, *level=None*, ***kwargs*)

Return whether any element is True, potentially over an axis.

Returns False unless there is at least one element within a series or along a Dataframe axis that is True or equivalent (e.g. non-zero or non-empty).

Parameters

axis [{0 or 'index', 1 or 'columns', None}, default 0] Indicate which axis or axes should be reduced.

- 0 / 'index' : reduce the index, return a Series whose index is the original column labels.

- 1 / 'columns' : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be False, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

****kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series If level is specified, then, Series is returned; otherwise, scalar is returned.

See also:

`numpy.any` Numpy version of this method.

`Series.any` Return whether any element is True.

`Series.all` Return whether all elements are True.

`DataFrame.any` Return whether any element is True over requested axis.

`DataFrame.all` Return whether all elements are True over requested axis.

Examples

Series

For Series input, the output is a scalar indicating whether any element is True.

```
>>> pd.Series([False, False]).any()
False
>>> pd.Series([True, False]).any()
True
>>> pd.Series([]).any()
False
>>> pd.Series([np.nan]).any()
False
>>> pd.Series([np.nan]).any(skipna=False)
True
```

DataFrame

Whether each column contains at least one True element (the default).

```
>>> df = pd.DataFrame({"A": [1, 2], "B": [0, 2], "C": [0, 0]})
>>> df
   A  B  C
0  1  0  0
1  2  2  0
```

```
>>> df.any()
A     True
B     True
C    False
dtype: bool
```

Aggregating over the columns.

```
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 2]})
>>> df
       A  B
0   True  1
1  False  2
```

```
>>> df.any(axis='columns')
0    True
1    True
dtype: bool
```

```
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 0]})
>>> df
       A  B
0   True  1
1  False  0
```

```
>>> df.any(axis='columns')
0    True
1    False
dtype: bool
```

Aggregating over the entire DataFrame with `axis=None`.

```
>>> df.any(axis=None)
True
```

any for an empty DataFrame is an empty Series.

```
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```

pandas.Series.append

`Series.`**`append`**(*to_append*, *ignore_index=False*, *verify_integrity=False*)

Concatenate two or more Series.

Parameters

to_append [Series or list/tuple of Series] Series to append with self.

ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, . . . , n - 1.

verify_integrity [bool, default False] If True, raise Exception on creating index with duplicates.

Returns

Series Concatenated Series.

See also:

`concat` General function to concatenate DataFrame or Series objects.

Notes

Iteratively appending to a Series can be more computationally intensive than a single concatenate. A better solution is to append values to a list and then concatenate the list with the original Series all at once.

Examples

```
>>> s1 = pd.Series([1, 2, 3])
>>> s2 = pd.Series([4, 5, 6])
>>> s3 = pd.Series([4, 5, 6], index=[3, 4, 5])
>>> s1.append(s2)
0    1
1    2
2    3
0    4
1    5
2    6
dtype: int64
```

```
>>> s1.append(s3)
0    1
1    2
2    3
3    4
4    5
5    6
dtype: int64
```

With *ignore_index* set to True:

```
>>> s1.append(s2, ignore_index=True)
0    1
1    2
2    3
3    4
4    5
5    6
dtype: int64
```

With *verify_integrity* set to True:

```
>>> s1.append(s2, verify_integrity=True)
Traceback (most recent call last):
...
ValueError: Indexes have overlapping values: [0, 1, 2]
```

pandas.Series.apply

Series.**apply**(*func*, *convert_dtype=True*, *args=()*, ***kwds*)

Invoke function on values of Series.

Can be ufunc (a NumPy function that applies to the entire Series) or a Python function that only works on single values.

Parameters

func [function] Python function or NumPy ufunc to apply.

convert_dtype [bool, default True] Try to find better dtype for elementwise function results. If False, leave as dtype=object.

args [tuple] Positional arguments passed to func after the series value.

****kwds** Additional keyword arguments passed to func.

Returns

Series or DataFrame If func returns a Series object the result will be a DataFrame.

See also:

Series.map For element-wise operations.

Series.agg Only perform aggregating type operations.

Series.transform Only perform transforming type operations.

Examples

Create a series with typical summer temperatures for each city.

```
>>> s = pd.Series([20, 21, 12],
...               index=['London', 'New York', 'Helsinki'])
>>> s
London      20
New York    21
Helsinki    12
dtype: int64
```

Square the values by defining a function and passing it as an argument to `apply()`.

```
>>> def square(x):
...     return x ** 2
>>> s.apply(square)
London      400
New York    441
Helsinki    144
dtype: int64
```

Square the values by passing an anonymous function as an argument to `apply()`.

```
>>> s.apply(lambda x: x ** 2)
London      400
New York    441
Helsinki    144
dtype: int64
```

Define a custom function that needs additional positional arguments and pass these additional arguments using the `args` keyword.

```
>>> def subtract_custom_value(x, custom_value):
...     return x - custom_value
```

```
>>> s.apply(subtract_custom_value, args=(5,))
London      15
New York    16
Helsinki     7
dtype: int64
```

Define a custom function that takes keyword arguments and pass these arguments to `apply`.

```
>>> def add_custom_values(x, **kwargs):
...     for month in kwargs:
...         x += kwargs[month]
...     return x
```

```
>>> s.apply(add_custom_values, june=30, july=20, august=25)
London      95
New York    96
Helsinki    87
dtype: int64
```

Use a function from the Numpy library.

```
>>> s.apply(np.log)
London      2.995732
New York    3.044522
Helsinki    2.484907
dtype: float64
```

pandas.Series.argmax

Series.**argmax**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return int position of the largest value in the Series.

If the maximum is achieved in multiple locations, the first row position is returned.

Parameters

axis [{None}] Dummy argument for consistency with Series.

skipna [bool, default True] Exclude NA/null values when showing the result.

***args, **kwargs** Additional arguments and keywords for compatibility with NumPy.

Returns

int Row position of the maximum value.

See also:

Series.argmax Return position of the maximum value.

Series.argmin Return position of the minimum value.

numpy.ndarray.argmax Equivalent method for numpy arrays.

Series.idxmax Return index label of the maximum values.

Series.idxmin Return index label of the minimum values.

Examples

Consider dataset containing cereal calories

```
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,
...                'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
>>> s
Corn Flakes              100.0
Almond Delight           110.0
Cinnamon Toast Crunch    120.0
Cocoa Puff               110.0
dtype: float64
```

```
>>> s.argmax()
2
>>> s.argmin()
0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.

pandas.Series.argmin

Series.**argmin**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return int position of the smallest value in the Series.

If the minimum is achieved in multiple locations, the first row position is returned.

Parameters

axis [{None}] Dummy argument for consistency with Series.

skipna [bool, default True] Exclude NA/null values when showing the result.

***args, **kwargs** Additional arguments and keywords for compatibility with NumPy.

Returns

int Row position of the minimum value.

See also:

Series.argmin Return position of the minimum value.

Series.argmax Return position of the maximum value.

numpy.ndarray.argmin Equivalent method for numpy arrays.

Series.idxmax Return index label of the maximum values.

Series.idxmin Return index label of the minimum values.

Examples

Consider dataset containing cereal calories

```
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,
...                'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
>>> s
Corn Flakes              100.0
Almond Delight           110.0
Cinnamon Toast Crunch    120.0
Cocoa Puff               110.0
dtype: float64
```

```
>>> s.argmax()
2
>>> s.argmin()
0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.

pandas.Series.argsort

`Series.`**`argsort`**(*axis=0*, *kind='quicksort'*, *order=None*)

Return the integer indices that would sort the Series values.

Override ndarray.argsort. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values.

Parameters

axis [{0 or "index"}] Has no effect but is accepted for compatibility with numpy.

kind [{'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'] Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm.

order [None] Has no effect but is accepted for compatibility with numpy.

Returns

Series Positions of values within the sort order with -1 indicating nan values.

See also:

numpy.ndarray.argsort Returns the indices that would sort this array.

pandas.Series.asfreq

`Series.`**`asfreq`**(*freq*, *method=None*, *how=None*, *normalize=False*, *fill_value=None*)

Convert TimeSeries to specified frequency.

Optionally provide filling method to pad/backfill missing values.

Returns the original data conformed to a new index with the specified frequency. `resample` is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

Parameters

freq [DateOffset or str] Frequency DateOffset or string.

method [{'backfill'/'bfill', 'pad'/'ffill'}, default None] Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):

- 'pad' / 'ffill': propagate last valid observation forward to next valid
- 'backfill' / 'bfill': use NEXT valid observation to fill.

how [{'start', 'end'}, default end] For PeriodIndex only (see PeriodIndex.asfreq).

normalize [bool, default False] Whether to reset output index to midnight.

fill_value [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

Returns

Same type as caller Object converted to the specified frequency.

See also:

reindex Conform DataFrame to new index with optional filling logic.

Notes

To learn more about the frequency strings, please see this link.

Examples

Start by creating a series with 4 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
                     s
2000-01-01 00:00:00    0.0
2000-01-01 00:01:00    NaN
2000-01-01 00:02:00    2.0
2000-01-01 00:03:00    3.0
```

Upsample the series into 30 second bins.

```
>>> df.asfreq(freq='30S')
                     s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    NaN
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    NaN
2000-01-01 00:03:00    3.0
```

Upsample again, providing a `fill value`.

```
>>> df.asfreq(freq='30S', fill_value=9.0)
                     s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    9.0
```

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```
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    9.0
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    9.0
2000-01-01 00:03:00    3.0
```

Upsample again, providing a `method`.

```
>>> df.asfreq(freq='30S', method='bfill')
                     s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  2.0
2000-01-01 00:02:00  2.0
2000-01-01 00:02:30  3.0
2000-01-01 00:03:00  3.0
```

pandas.Series.asof

Series.**asof**(*where*, *subset=None*)

Return the last row(s) without any NaNs before *where*.

The last row (for each element in *where*, if list) without any NaN is taken. In case of a *DataFrame*, the last row without NaN considering only the subset of columns (if not *None*)

If there is no good value, NaN is returned for a Series or a Series of NaN values for a DataFrame

Parameters

where [date or array-like of dates] Date(s) before which the last row(s) are returned.

subset [str or array-like of str, default *None*] For DataFrame, if not *None*, only use these columns to check for NaNs.

Returns

scalar, Series, or DataFrame The return can be:

- scalar : when *self* is a Series and *where* is a scalar
- Series: when *self* is a Series and *where* is an array-like, or when *self* is a DataFrame and *where* is a scalar
- DataFrame : when *self* is a DataFrame and *where* is an array-like

Return scalar, Series, or DataFrame.

See also:

merge_asof Perform an asof merge. Similar to left join.

Notes

Dates are assumed to be sorted. Raises if this is not the case.

Examples

A Series and a scalar *where*.

```
>>> s = pd.Series([1, 2, np.nan, 4], index=[10, 20, 30, 40])
>>> s
10    1.0
20    2.0
30    NaN
40    4.0
dtype: float64
```

```
>>> s.asof(20)
2.0
```

For a sequence *where*, a Series is returned. The first value is NaN, because the first element of *where* is before the first index value.

```
>>> s.asof([5, 20])
5     NaN
20    2.0
dtype: float64
```

Missing values are not considered. The following is `2.0`, not NaN, even though NaN is at the index location for `30`.

```
>>> s.asof(30)
2.0
```

Take all columns into consideration

```
>>> df = pd.DataFrame({'a': [10, 20, 30, 40, 50],
...                    'b': [None, None, None, None, 500]},
...                   index=pd.DatetimeIndex(['2018-02-27 09:01:00',
...                                           '2018-02-27 09:02:00',
...                                           '2018-02-27 09:03:00',
...                                           '2018-02-27 09:04:00',
...                                           '2018-02-27 09:05:00']))
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                           '2018-02-27 09:04:30']))
                     a   b
2018-02-27 09:03:30 NaN NaN
2018-02-27 09:04:30 NaN NaN
```

Take a single column into consideration

```
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                           '2018-02-27 09:04:30']),
...         subset=['a'])
                       a   b
2018-02-27 09:03:30   30.0 NaN
2018-02-27 09:04:30   40.0 NaN
```

pandas.Series.astype

Series.**astype**(*dtype*, *copy=True*, *errors='raise'*)

Cast a pandas object to a specified dtype `dtype`.

Parameters

dtype [data type, or dict of column name -> data type] Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use {col: dtype, ...}, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame's columns to column-specific types.

copy [bool, default True] Return a copy when `copy=True` (be very careful setting `copy=False` as changes to values then may propagate to other pandas objects).

errors [{'raise', 'ignore'}, default 'raise'] Control raising of exceptions on invalid data for provided dtype.

- `raise` : allow exceptions to be raised
- `ignore` : suppress exceptions. On error return original object.

Returns

casted [same type as caller]

See also:

to_datetime Convert argument to datetime.

to_timedelta Convert argument to timedelta.

to_numeric Convert argument to a numeric type.

numpy.ndarray.astype Cast a numpy array to a specified type.

Examples

Create a DataFrame:

```
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```

Cast all columns to int32:

```
>>> df.astype('int32').dtypes
col1    int32
col2    int32
dtype: object
```

Cast col1 to int32 using a dictionary:

```
>>> df.astype({'col1': 'int32'}).dtypes
col1    int32
col2    int64
dtype: object
```

Create a series:

```
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0    1
1    2
dtype: int32
>>> ser.astype('int64')
0    1
1    2
dtype: int64
```

Convert to categorical type:

```
>>> ser.astype('category')
0    1
1    2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:

```
>>> cat_dtype = pd.api.types.CategoricalDtype(
...     categories=[2, 1], ordered=True)
>>> ser.astype(cat_dtype)
0    1
1    2
dtype: category
Categories (2, int64): [2 < 1]
```

Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```
>>> s1 = pd.Series([1, 2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
>>> s1  # note that s1[0] has changed too
0    10
1     2
dtype: int64
```

Create a series of dates:

```
>>> ser_date = pd.Series(pd.date_range('20200101', periods=3))
>>> ser_date
0   2020-01-01
1   2020-01-02
2   2020-01-03
dtype: datetime64[ns]
```

Datetimes are localized to UTC first before converting to the specified timezone:

```
>>> ser_date.astype('datetime64[ns, US/Eastern]')
0   2019-12-31 19:00:00-05:00
1   2020-01-01 19:00:00-05:00
2   2020-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

pandas.Series.at_time

Series.**at_time**(*time*, *asof=False*, *axis=None*)

Select values at particular time of day (e.g., 9:30AM).

Parameters

time [datetime.time or str]

axis [{0 or 'index', 1 or 'columns'}, default 0] New in version 0.24.0.

Returns

Series or DataFrame

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

between_time Select values between particular times of the day.

first Select initial periods of time series based on a date offset.

last Select final periods of time series based on a date offset.

DatetimeIndex.indexer_at_time Get just the index locations for values at particular time of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
                     A
2018-04-09 00:00:00  1
2018-04-09 12:00:00  2
2018-04-10 00:00:00  3
2018-04-10 12:00:00  4
```

```
>>> ts.at_time('12:00')
                     A
2018-04-09 12:00:00  2
2018-04-10 12:00:00  4
```

pandas.Series.autocorr

Series.**autocorr**(*lag=1*)

Compute the lag-N autocorrelation.

This method computes the Pearson correlation between the Series and its shifted self.

Parameters

lag [int, default 1] Number of lags to apply before performing autocorrelation.

Returns

float The Pearson correlation between self and self.shift(lag).

See also:

Series.corr Compute the correlation between two Series.

Series.shift Shift index by desired number of periods.

DataFrame.corr Compute pairwise correlation of columns.

DataFrame.corrwith Compute pairwise correlation between rows or columns of two DataFrame objects.

Notes

If the Pearson correlation is not well defined return 'NaN'.

Examples

```
>>> s = pd.Series([0.25, 0.5, 0.2, -0.05])
>>> s.autocorr()
0.10355...
>>> s.autocorr(lag=2)
-0.99999...
```

If the Pearson correlation is not well defined, then 'NaN' is returned.

```
>>> s = pd.Series([1, 0, 0, 0])
>>> s.autocorr()
nan
```

pandas.Series.backfill

Series.**backfill**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *DataFrame.fillna()* with `method='bfill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.Series.between

Series.**between**(*left*, *right*, *inclusive=True*)

Return boolean Series equivalent to left <= series <= right.

This function returns a boolean vector containing *True* wherever the corresponding Series element is between the boundary values *left* and *right*. NA values are treated as *False*.

Parameters

left [scalar or list-like] Left boundary.

right [scalar or list-like] Right boundary.

inclusive [bool, default True] Include boundaries.

Returns

Series Series representing whether each element is between left and right (inclusive).

See also:

`Series.gt` Greater than of series and other.

`Series.lt` Less than of series and other.

Notes

This function is equivalent to `(left <= ser) & (ser <= right)`

Examples

```
>>> s = pd.Series([2, 0, 4, 8, np.nan])
```

Boundary values are included by default:

```
>>> s.between(1, 4)
0     True
1    False
2     True
3    False
4    False
dtype: bool
```

With *inclusive* set to `False` boundary values are excluded:

```
>>> s.between(1, 4, inclusive=False)
0     True
1    False
2    False
3    False
4    False
dtype: bool
```

left and *right* can be any scalar value:

```
>>> s = pd.Series(['Alice', 'Bob', 'Carol', 'Eve'])
>>> s.between('Anna', 'Daniel')
0    False
1     True
2     True
3    False
dtype: bool
```

pandas.Series.between_time

`Series.`**`between_time`**(*start_time*, *end_time*, *include_start=True*, *include_end=True*, *axis=None*)

Select values between particular times of the day (e.g., 9:00-9:30 AM).

By setting `start_time` to be later than `end_time`, you can get the times that are *not* between the two times.

Parameters

start_time [datetime.time or str] Initial time as a time filter limit.

end_time [datetime.time or str] End time as a time filter limit.

include_start [bool, default True] Whether the start time needs to be included in the result.

include_end [bool, default True] Whether the end time needs to be included in the result.

axis [{0 or 'index', 1 or 'columns'}, default 0] Determine range time on index or columns value.

New in version 0.24.0.

Returns

Series or DataFrame Data from the original object filtered to the specified dates range.

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

at_time Select values at a particular time of the day.

first Select initial periods of time series based on a date offset.

last Select final periods of time series based on a date offset.

DatetimeIndex.indexer_between_time Get just the index locations for values between particular times of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
                     A
2018-04-09 00:00:00  1
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3
2018-04-12 01:00:00  4
```

```
>>> ts.between_time('0:15', '0:45')
                     A
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3
```

You get the times that are *not* between two times by setting `start_time` later than `end_time`:

```
>>> ts.between_time('0:45', '0:15')
                     A
2018-04-09 00:00:00  1
2018-04-12 01:00:00  4
```

pandas.Series.bfill

Series.**bfill**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *DataFrame.fillna()* with `method='bfill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.Series.bool

Series.**bool**()

Return the bool of a single element Series or DataFrame.

This must be a boolean scalar value, either True or False. It will raise a ValueError if the Series or DataFrame does not have exactly 1 element, or that element is not boolean (integer values 0 and 1 will also raise an exception).

Returns

bool The value in the Series or DataFrame.

See also:

Series.astype Change the data type of a Series, including to boolean.

DataFrame.astype Change the data type of a DataFrame, including to boolean.

numpy.bool_ NumPy boolean data type, used by pandas for boolean values.

Examples

The method will only work for single element objects with a boolean value:

```
>>> pd.Series([True]).bool()
True
>>> pd.Series([False]).bool()
False
```

```
>>> pd.DataFrame({'col': [True]}).bool()
True
>>> pd.DataFrame({'col': [False]}).bool()
False
```

pandas.Series.cat

Series.**cat**()

Accessor object for categorical properties of the Series values.

Be aware that assigning to *categories* is a inplace operation, while all methods return new categorical data per default (but can be called with *inplace=True*).

Parameters

data [Series or CategoricalIndex]

Examples

```
>>> s = pd.Series(list("abbccc")).astype("category")
>>> s
0    a
1    b
2    b
3    c
4    c
5    c
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

```
>>> s.cat.categories
Index(['a', 'b', 'c'], dtype='object')
```

```
>>> s.cat.rename_categories(list("cba"))
0    c
1    b
2    b
3    a
4    a
5    a
dtype: category
Categories (3, object): ['c', 'b', 'a']
```

```
>>> s.cat.reorder_categories(list("cba"))
0    a
1    b
2    b
3    c
4    c
5    c
dtype: category
Categories (3, object): ['c', 'b', 'a']
```

```
>>> s.cat.add_categories(["d", "e"])
0    a
1    b
2    b
3    c
4    c
5    c
dtype: category
Categories (5, object): ['a', 'b', 'c', 'd', 'e']
```

```
>>> s.cat.remove_categories(["a", "c"])
0    NaN
1      b
2      b
3    NaN
4    NaN
5    NaN
dtype: category
Categories (1, object): ['b']
```

```
>>> s1 = s.cat.add_categories(["d", "e"])
>>> s1.cat.remove_unused_categories()
0    a
1    b
2    b
3    c
4    c
5    c
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

```
>>> s.cat.set_categories(list("abcde"))
0    a
1    b
2    b
3    c
4    c
5    c
dtype: category
Categories (5, object): ['a', 'b', 'c', 'd', 'e']
```

```
>>> s.cat.as_ordered()
0    a
1    b
2    b
3    c
4    c
5    c
dtype: category
Categories (3, object): ['a' < 'b' < 'c']
```

```
>>> s.cat.as_unordered()
0    a
1    b
2    b
3    c
4    c
5    c
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

pandas.Series.clip

Series.**clip**(*lower=None*, *upper=None*, *axis=None*, *inplace=False*, **args*, ***kwargs*)

Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

Parameters

lower [float or array_like, default None] Minimum threshold value. All values below this threshold will be set to it.

upper [float or array_like, default None] Maximum threshold value. All values above this threshold will be set to it.

axis [int or str axis name, optional] Align object with lower and upper along the given axis.

inplace [bool, default False] Whether to perform the operation in place on the data.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with numpy.

Returns

Series or DataFrame or None Same type as calling object with the values outside the clip boundaries replaced or None if `inplace=True`.

See also:

Series.clip Trim values at input threshold in series.

DataFrame.clip Trim values at input threshold in dataframe.

numpy.clip Clip (limit) the values in an array.

Examples

```
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
   col_0  col_1
0      9     -2
1     -3     -7
2      0      6
3     -1      8
4      5     -5
```

Clips per column using lower and upper thresholds:

```
>>> df.clip(-4, 6)
   col_0  col_1
0      6     -2
1     -3     -4
2      0      6
3     -1      6
4      5     -4
```

Clips using specific lower and upper thresholds per column element:

```
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0    2
1   -4
2   -1
3    6
4    3
dtype: int64
```

```
>>> df.clip(t, t + 4, axis=0)
   col_0  col_1
0      6      2
1     -3     -4
2      0      3
```

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```
3       6       8
4       5       3
```

pandas.Series.combine

Series.**combine**(*other*, *func*, *fill_value=None*)

Combine the Series with a Series or scalar according to *func*.

Combine the Series and *other* using *func* to perform elementwise selection for combined Series. *fill_value* is assumed when value is missing at some index from one of the two objects being combined.

Parameters

other [Series or scalar] The value(s) to be combined with the *Series*.

func [function] Function that takes two scalars as inputs and returns an element.

fill_value [scalar, optional] The value to assume when an index is missing from one Series or the other. The default specifies to use the appropriate NaN value for the underlying dtype of the Series.

Returns

Series The result of combining the Series with the other object.

See also:

Series.combine_first Combine Series values, choosing the calling Series' values first.

Examples

Consider 2 Datasets `s1` and `s2` containing highest clocked speeds of different birds.

```
>>> s1 = pd.Series({'falcon': 330.0, 'eagle': 160.0})
>>> s1
falcon    330.0
eagle     160.0
dtype: float64
>>> s2 = pd.Series({'falcon': 345.0, 'eagle': 200.0, 'duck': 30.0})
>>> s2
falcon    345.0
eagle     200.0
duck       30.0
dtype: float64
```

Now, to combine the two datasets and view the highest speeds of the birds across the two datasets

```
>>> s1.combine(s2, max)
duck        NaN
eagle     200.0
falcon    345.0
dtype: float64
```

In the previous example, the resulting value for duck is missing, because the maximum of a NaN and a float is a NaN. So, in the example, we set `fill_value=0`, so the maximum value returned will be the value from some dataset.

```
>>> s1.combine(s2, max, fill_value=0)
duck       30.0
eagle     200.0
falcon    345.0
dtype: float64
```

pandas.Series.combine_first

Series.**combine_first**(*other*)

Combine Series values, choosing the calling Series's values first.

Parameters

other [Series] The value(s) to be combined with the *Series*.

Returns

Series The result of combining the Series with the other object.

See also:

Series.combine Perform elementwise operation on two Series using a given function.

Notes

Result index will be the union of the two indexes.

Examples

```
>>> s1 = pd.Series([1, np.nan])
>>> s2 = pd.Series([3, 4])
>>> s1.combine_first(s2)
0    1.0
1    4.0
dtype: float64
```

pandas.Series.compare

Series.**compare**(*other*, *align_axis=1*, *keep_shape=False*, *keep_equal=False*)

Compare to another Series and show the differences.

New in version 1.1.0.

Parameters

other [Series] Object to compare with.

align_axis [{0 or 'index', 1 or 'columns'}, default 1] Determine which axis to align the comparison on.

- **0, or 'index'** [Resulting differences are stacked vertically] with rows drawn alternately from self and other.
- **1, or 'columns'** [Resulting differences are aligned horizontally] with columns drawn alternately from self and other.

keep_shape [bool, default False] If true, all rows and columns are kept. Otherwise, only the ones with different values are kept.

keep_equal [bool, default False] If true, the result keeps values that are equal. Otherwise, equal values are shown as NaNs.

Returns

Series or DataFrame If axis is 0 or 'index' the result will be a Series. The resulting index will be a MultiIndex with 'self' and 'other' stacked alternately at the inner level.

If axis is 1 or 'columns' the result will be a DataFrame. It will have two columns namely 'self' and 'other'.

See also:

DataFrame.compare Compare with another DataFrame and show differences.

Notes

Matching NaNs will not appear as a difference.

Examples

```
>>> s1 = pd.Series(["a", "b", "c", "d", "e"])
>>> s2 = pd.Series(["a", "a", "c", "b", "e"])
```

Align the differences on columns

```
>>> s1.compare(s2)
  self other
1    b     a
3    d     b
```

Stack the differences on indices

```
>>> s1.compare(s2, align_axis=0)
1  self     b
   other    a
3  self     d
   other    b
dtype: object
```

Keep all original rows

```
>>> s1.compare(s2, keep_shape=True)
  self other
0  NaN   NaN
1    b     a
2  NaN   NaN
3    d     b
4  NaN   NaN
```

Keep all original rows and also all original values

```
>>> s1.compare(s2, keep_shape=True, keep_equal=True)
  self other
0    a     a
1    b     a
2    c     c
3    d     b
4    e     e
```

pandas.Series.convert_dtypes

Series.**convert_dtypes**(*infer_objects=True*, *convert_string=True*, *convert_integer=True*, *convert_boolean=True*, *convert_floating=True*)

Convert columns to best possible dtypes using dtypes supporting `pd.NA`.

New in version 1.0.0.

Parameters

infer_objects [bool, default True] Whether object dtypes should be converted to the best possible types.

convert_string [bool, default True] Whether object dtypes should be converted to `StringDtype()`.

convert_integer [bool, default True] Whether, if possible, conversion can be done to integer extension types.

convert_boolean [bool, defaults True] Whether object dtypes should be converted to `BooleanDtypes()`.

convert_floating [bool, defaults True] Whether, if possible, conversion can be done to floating extension types. If *convert_integer* is also True, preference will be give to integer dtypes if the floats can be faithfully casted to integers.

New in version 1.2.0.

Returns

Series or DataFrame Copy of input object with new dtype.

See also:

infer_objects Infer dtypes of objects.

to_datetime Convert argument to datetime.

to_timedelta Convert argument to timedelta.

to_numeric Convert argument to a numeric type.

Notes

By default, `convert_dtypes` will attempt to convert a Series (or each Series in a DataFrame) to dtypes that support `pd.NA`. By using the options `convert_string`, `convert_integer`, `convert_boolean` and `convert_boolean`, it is possible to turn off individual conversions to `StringDtype`, the integer extension types, `BooleanDtype` or floating extension types, respectively.

For object-dtyped columns, if `infer_objects` is `True`, use the inference rules as during normal Series/DataFrame construction. Then, if possible, convert to `StringDtype`, `BooleanDtype` or an appropriate integer or floating extension type, otherwise leave as `object`.

If the dtype is integer, convert to an appropriate integer extension type.

If the dtype is numeric, and consists of all integers, convert to an appropriate integer extension type. Otherwise, convert to an appropriate floating extension type.

Changed in version 1.2: Starting with pandas 1.2, this method also converts float columns to the nullable floating extension type.

In the future, as new dtypes are added that support `pd.NA`, the results of this method will change to support those new dtypes.

Examples

```
>>> df = pd.DataFrame(
...     {
...         "a": pd.Series([1, 2, 3], dtype=np.dtype("int32")),
...         "b": pd.Series(["x", "y", "z"], dtype=np.dtype("O")),
...         "c": pd.Series([True, False, np.nan], dtype=np.dtype("O")),
...         "d": pd.Series(["h", "i", np.nan], dtype=np.dtype("O")),
...         "e": pd.Series([10, np.nan, 20], dtype=np.dtype("float")),
...         "f": pd.Series([np.nan, 100.5, 200], dtype=np.dtype("float")),
...     }
... )
```

Start with a DataFrame with default dtypes.

```
>>> df
   a  b      c    d     e      f
0  1  x   True    h  10.0    NaN
1  2  y  False    i   NaN  100.5
2  3  z    NaN  NaN  20.0  200.0
```

```
>>> df.dtypes
a      int32
b     object
c     object
d     object
e    float64
f    float64
dtype: object
```

Convert the DataFrame to use best possible dtypes.

```
>>> dfn = df.convert_dtypes()
>>> dfn
   a  b      c     d     e      f
```

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```
0  1  x   True     h    10   <NA>
1  2  y  False     i  <NA>  100.5
2  3  z   <NA>  <NA>    20  200.0
```

```
>>> dfn.dtypes
a      Int32
b     string
c    boolean
d     string
e      Int64
f    Float64
dtype: object
```

Start with a Series of strings and missing data represented by `np.nan`.

```
>>> s = pd.Series(["a", "b", np.nan])
>>> s
0      a
1      b
2    NaN
dtype: object
```

Obtain a Series with dtype `StringDtype`.

```
>>> s.convert_dtypes()
0       a
1       b
2    <NA>
dtype: string
```

pandas.Series.copy

`Series.`**`copy`**(*deep=True*)

Make a copy of this object's indices and data.

When `deep=True` (default), a new object will be created with a copy of the calling object's data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).

When `deep=False`, a new object will be created without copying the calling object's data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

Parameters

deep [bool, default True] Make a deep copy, including a copy of the data and the indices. With `deep=False` neither the indices nor the data are copied.

Returns

copy [Series or DataFrame] Object type matches caller.

Notes

When `deep=True`, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to *copy.deepcopy* in the Standard Library, which recursively copies object data (see examples below).

While `Index` objects are copied when `deep=True`, the underlying numpy array is not copied for performance reasons. Since `Index` is immutable, the underlying data can be safely shared and a copy is not needed.

Examples

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> s
a    1
b    2
dtype: int64
```

```
>>> s_copy = s.copy()
>>> s_copy
a    1
b    2
dtype: int64
```

Shallow copy versus default (deep) copy:

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> deep = s.copy()
>>> shallow = s.copy(deep=False)
```

Shallow copy shares data and index with original.

```
>>> s is shallow
False
>>> s.values is shallow.values and s.index is shallow.index
True
```

Deep copy has own copy of data and index.

```
>>> s is deep
False
>>> s.values is deep.values or s.index is deep.index
False
```

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

```
>>> s[0] = 3
>>> shallow[1] = 4
>>> s
a    3
b    4
dtype: int64
>>> shallow
a    3
b    4
dtype: int64
```

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```
>>> deep
a    1
b    2
dtype: int64
```

Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

```
>>> s = pd.Series([[1, 2], [3, 4]])
>>> deep = s.copy()
>>> s[0][0] = 10
>>> s
0    [10, 2]
1     [3, 4]
dtype: object
>>> deep
0    [10, 2]
1     [3, 4]
dtype: object
```

pandas.Series.corr

Series.**corr**(*other*, *method='pearson'*, *min_periods=None*)

Compute correlation with *other* Series, excluding missing values.

Parameters

other [Series] Series with which to compute the correlation.

method [{'pearson', 'kendall', 'spearman'} or callable] Method used to compute correlation:

- pearson : Standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- callable: Callable with input two 1d ndarrays and returning a float.

New in version 0.24.0: Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable's behavior.

min_periods [int, optional] Minimum number of observations needed to have a valid result.

Returns

float Correlation with other.

See also:

DataFrame.corr Compute pairwise correlation between columns.

DataFrame.corrwith Compute pairwise correlation with another DataFrame or Series.

Examples

```
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
>>> s1 = pd.Series([.2, .0, .6, .2])
>>> s2 = pd.Series([.3, .6, .0, .1])
>>> s1.corr(s2, method=histogram_intersection)
0.3
```

pandas.Series.count

Series.**count**(*level=None*)

Return number of non-NA/null observations in the Series.

Parameters

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series.

Returns

int or Series (if level specified) Number of non-null values in the Series.

See also:

DataFrame.count Count non-NA cells for each column or row.

Examples

```
>>> s = pd.Series([0.0, 1.0, np.nan])
>>> s.count()
2
```

pandas.Series.cov

Series.**cov**(*other*, *min_periods=None*, *ddof=1*)

Compute covariance with Series, excluding missing values.

Parameters

other [Series] Series with which to compute the covariance.

min_periods [int, optional] Minimum number of observations needed to have a valid result.

ddof [int, default 1] Delta degrees of freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

New in version 1.1.0.

Returns

float Covariance between Series and other normalized by N-1 (unbiased estimator).

See also:

DataFrame.cov Compute pairwise covariance of columns.

Examples

```
>>> s1 = pd.Series([0.90010907, 0.13484424, 0.62036035])
>>> s2 = pd.Series([0.12528585, 0.26962463, 0.51111198])
>>> s1.cov(s2)
-0.01685762652715874
```

pandas.Series.cummax

Series.**cummax**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series Return cumulative maximum of scalar or Series.

See also:

core.window.Expanding.max Similar functionality but ignores NaN values.

Series.max Return the maximum over Series axis.

Series.cummax Return cumulative maximum over Series axis.

Series.cummin Return cumulative minimum over Series axis.

Series.cumsum Return cumulative sum over Series axis.

Series.cumprod Return cumulative product over Series axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummax()
0    2.0
1    NaN
2    5.0
3    5.0
4    5.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummax(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                   columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummax()
     A    B
0  2.0  1.0
1  3.0  NaN
2  3.0  1.0
```

To iterate over columns and find the maximum in each row, use `axis=1`

```
>>> df.cummax(axis=1)
     A    B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

pandas.Series.cummin

Series.**cummin**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series Return cumulative minimum of scalar or Series.

See also:

core.window.Expanding.min Similar functionality but ignores NaN values.

Series.min Return the minimum over Series axis.

Series.cummax Return cumulative maximum over Series axis.

Series.cummin Return cumulative minimum over Series axis.

Series.cumsum Return cumulative sum over Series axis.

Series.cumprod Return cumulative product over Series axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummin()
0    2.0
1    NaN
2    2.0
3   -1.0
4   -1.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummin(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummin()
     A    B
0  2.0  1.0
1  2.0  NaN
2  1.0  0.0
```

To iterate over columns and find the minimum in each row, use `axis=1`

```
>>> df.cummin(axis=1)
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

pandas.Series.cumprod

`Series.`**`cumprod`**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series Return cumulative product of scalar or Series.

See also:

core.window.Expanding.prod Similar functionality but ignores NaN values.

Series.prod Return the product over Series axis.

Series.cummax Return cumulative maximum over Series axis.

Series.cummin Return cumulative minimum over Series axis.

Series.cumsum Return cumulative sum over Series axis.

Series.cumprod Return cumulative product over Series axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumprod()
0     2.0
1     NaN
2    10.0
3   -10.0
4    -0.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumprod(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumprod()
     A    B
0  2.0  1.0
1  6.0  NaN
2  6.0  0.0
```

To iterate over columns and find the product in each row, use `axis=1`

```
>>> df.cumprod(axis=1)
     A    B
0  2.0  2.0
1  3.0  NaN
2  1.0  0.0
```

pandas.Series.cumsum

`Series.`**`cumsum`**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series Return cumulative sum of scalar or Series.

See also:

`core.window.Expanding.sum` Similar functionality but ignores `NaN` values.

`Series.sum` Return the sum over Series axis.

`Series.cummax` Return cumulative maximum over Series axis.

`Series.cummin` Return cumulative minimum over Series axis.

`Series.cumsum` Return cumulative sum over Series axis.

`Series.cumprod` Return cumulative product over Series axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumsum()
0    2.0
1    NaN
2    7.0
3    6.0
4    6.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumsum(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumsum()
     A    B
0  2.0  1.0
1  5.0  NaN
2  6.0  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```
>>> df.cumsum(axis=1)
     A    B
```

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```
0  2.0  3.0
1  3.0  NaN
2  1.0  1.0
```

pandas.Series.describe

Series.**describe**(*percentiles=None*, *include=None*, *exclude=None*, *datetime_is_numeric=False*)

Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding `NaN` values.

Analyzes both numeric and object series, as well as `DataFrame` column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

Parameters

percentiles [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is `[.25, .5, .75]`, which returns the 25th, 50th, and 75th percentiles.

include ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for `Series`. Here are the options:

- 'all' : All columns of the input will be included in the output.
- A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use `'category'`
- None (default) : The result will include all numeric columns.

exclude [list-like of dtypes or None (default), optional,] A black list of data types to omit from the result. Ignored for `Series`. Here are the options:

- A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To exclude pandas categorical columns, use `'category'`
- None (default) : The result will exclude nothing.

datetime_is_numeric [bool, default False] Whether to treat datetime dtypes as numeric. This affects statistics calculated for the column. For DataFrame input, this also controls whether datetime columns are included by default.

New in version 1.1.0.

Returns

Series or DataFrame Summary statistics of the Series or Dataframe provided.

See also:

DataFrame.count Count number of non-NA/null observations.

DataFrame.max Maximum of the values in the object.

DataFrame.min Minimum of the values in the object.

DataFrame.mean Mean of the values.

DataFrame.std Standard deviation of the observations.

DataFrame.select_dtypes Subset of a DataFrame including/excluding columns based on their dtype.

Notes

For numeric data, the result's index will include `count`, `mean`, `std`, `min`, `max` as well as lower, `50` and upper percentiles. By default the lower percentile is `25` and the upper percentile is `75`. The `50` percentile is the same as the median.

For object data (e.g. strings or timestamps), the result's index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value's frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The *include* and *exclude* parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`.

Examples

Describing a numeric `Series`.

```
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
dtype: float64
```

Describing a categorical `Series`.

```
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count     4
unique    3
top       a
freq      2
dtype: object
```

Describing a timestamp `Series`.

```
>>> s = pd.Series([
...   np.datetime64("2000-01-01"),
...   np.datetime64("2010-01-01"),
...   np.datetime64("2010-01-01")
... ])
>>> s.describe(datetime_is_numeric=True)
count                      3
mean     2006-09-01 08:00:00
min      2000-01-01 00:00:00
25%      2004-12-31 12:00:00
50%      2010-01-01 00:00:00
75%      2010-01-01 00:00:00
max      2010-01-01 00:00:00
dtype: object
```

Describing a `DataFrame`. By default only numeric fields are returned.

```
>>> df = pd.DataFrame({'categorical': pd.Categorical(['d','e','f']),
...                    'numeric': [1, 2, 3],
...                    'object': ['a', 'b', 'c']
...                   })
>>> df.describe()
       numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%        1.5
50%        2.0
75%        2.5
max        3.0
```

Describing all columns of a `DataFrame` regardless of data type.

```
>>> df.describe(include='all')
       categorical  numeric object
count            3      3.0      3
unique           3      NaN      3
top              f      NaN      a
freq             1      NaN      1
mean           NaN      2.0    NaN
std            NaN      1.0    NaN
min            NaN      1.0    NaN
25%            NaN      1.5    NaN
50%            NaN      2.0    NaN
75%            NaN      2.5    NaN
max            NaN      3.0    NaN
```

Describing a column from a `DataFrame` by accessing it as an attribute.

```
>>> df.numeric.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
```

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```
75%      2.5
max      3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a `DataFrame` description.

```
>>> df.describe(include=[np.number])
       numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%        1.5
50%        2.0
75%        2.5
max        3.0
```

Including only string columns in a `DataFrame` description.

```
>>> df.describe(include=[object])
       object
count       3
unique      3
top         a
freq        1
```

Including only categorical columns from a `DataFrame` description.

```
>>> df.describe(include=['category'])
       categorical
count            3
unique           3
top              d
freq             1
```

Excluding numeric columns from a `DataFrame` description.

```
>>> df.describe(exclude=[np.number])
       categorical object
count            3      3
unique           3      3
top              f      a
freq             1      1
```

Excluding object columns from a `DataFrame` description.

```
>>> df.describe(exclude=[object])
       categorical  numeric
count            3      3.0
unique           3      NaN
top              f      NaN
freq             1      NaN
mean           NaN      2.0
std            NaN      1.0
min            NaN      1.0
25%            NaN      1.5
```

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```
50%            NaN      2.0
75%            NaN      2.5
max            NaN      3.0
```

pandas.Series.diff

Series.**diff**(*periods=1*)

First discrete difference of element.

Calculates the difference of a Series element compared with another element in the Series (default is element in previous row).

Parameters

periods [int, default 1] Periods to shift for calculating difference, accepts negative values.

Returns

Series First differences of the Series.

See also:

Series.pct_change Percent change over given number of periods.

Series.shift Shift index by desired number of periods with an optional time freq.

DataFrame.diff First discrete difference of object.

Notes

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`. The result is calculated according to current dtype in Series, however dtype of the result is always float64.

Examples

Difference with previous row

```
>>> s = pd.Series([1, 1, 2, 3, 5, 8])
>>> s.diff()
0    NaN
1    0.0
2    1.0
3    1.0
4    2.0
5    3.0
dtype: float64
```

Difference with 3rd previous row

```
>>> s.diff(periods=3)
0    NaN
1    NaN
2    NaN
3    2.0
4    4.0
```

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```
5    6.0
dtype: float64
```

Difference with following row

```
>>> s.diff(periods=-1)
0    0.0
1   -1.0
2   -1.0
3   -2.0
4   -3.0
5    NaN
dtype: float64
```

Overflow in input dtype

```
>>> s = pd.Series([1, 0], dtype=np.uint8)
>>> s.diff()
0      NaN
1    255.0
dtype: float64
```

pandas.Series.div

`Series.`**`div`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

`Series.rtruediv` Reverse of the Floating division operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
d    0.0
e    NaN
dtype: float64
```

pandas.Series.divide

`Series.`**`divide`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

`Series.rtruediv` Reverse of the Floating division operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
d    0.0
e    NaN
dtype: float64
```

pandas.Series.divmod

Series.**divmod**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Integer division and modulo of series and other, element-wise (binary operator *divmod*).

Equivalent to `divmod(series, other)`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

2-Tuple of Series The result of the operation.

See also:

Series.rdivmod Reverse of the Integer division and modulo operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divmod(b, fill_value=0)
(a    1.0
 b    NaN
 c    NaN
 d    0.0
 e    NaN
 dtype: float64,
 a    0.0
 b    NaN
 c    NaN
 d    0.0
 e    NaN
 dtype: float64)
```

pandas.Series.dot

`Series.dot(other)`

Compute the dot product between the Series and the columns of other.

This method computes the dot product between the Series and another one, or the Series and each columns of a DataFrame, or the Series and each columns of an array.

It can also be called using *self @ other* in Python >= 3.5.

Parameters

other [Series, DataFrame or array-like] The other object to compute the dot product with its columns.

Returns

scalar, Series or numpy.ndarray Return the dot product of the Series and other if other is a Series, the Series of the dot product of Series and each rows of other if other is a DataFrame or a numpy.ndarray between the Series and each columns of the numpy array.

See also:

DataFrame.dot Compute the matrix product with the DataFrame.

Series.mul Multiplication of series and other, element-wise.

Notes

The Series and other has to share the same index if other is a Series or a DataFrame.

Examples

```
>>> s = pd.Series([0, 1, 2, 3])
>>> other = pd.Series([-1, 2, -3, 4])
>>> s.dot(other)
8
>>> s @ other
8
>>> df = pd.DataFrame([[0, 1], [-2, 3], [4, -5], [6, 7]])
>>> s.dot(df)
0    24
1    14
dtype: int64
>>> arr = np.array([[0, 1], [-2, 3], [4, -5], [6, 7]])
>>> s.dot(arr)
array([24, 14])
```

pandas.Series.drop

Series.**drop**(*labels=None*, *axis=0*, *index=None*, *columns=None*, *level=None*, *inplace=False*, *errors='raise'*)

Return Series with specified index labels removed.

Remove elements of a Series based on specifying the index labels. When using a multi-index, labels on different levels can be removed by specifying the level.

Parameters

labels [single label or list-like] Index labels to drop.

axis [0, default 0] Redundant for application on Series.

index [single label or list-like] Redundant for application on Series, but 'index' can be used instead of 'labels'.

columns [single label or list-like] No change is made to the Series; use 'index' or 'labels' instead.

level [int or level name, optional] For MultiIndex, level for which the labels will be removed.

inplace [bool, default False] If True, do operation inplace and return None.

errors [{'ignore', 'raise'}, default 'raise'] If 'ignore', suppress error and only existing labels are dropped.

Returns

Series or None Series with specified index labels removed or None if `inplace=True`.

Raises

KeyError If none of the labels are found in the index.

See also:

Series.reindex Return only specified index labels of Series.

Series.dropna Return series without null values.

Series.drop_duplicates Return Series with duplicate values removed.

DataFrame.drop Drop specified labels from rows or columns.

Examples

```
>>> s = pd.Series(data=np.arange(3), index=['A', 'B', 'C'])
>>> s
A  0
B  1
C  2
dtype: int64
```

Drop labels B en C

```
>>> s.drop(labels=['B', 'C'])
A  0
dtype: int64
```

Drop 2nd level label in MultiIndex Series

```
>>> midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
...                              ['speed', 'weight', 'length']],
...                      codes=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
...                             [0, 1, 2, 0, 1, 2, 0, 1, 2]])
>>> s = pd.Series([45, 200, 1.2, 30, 250, 1.5, 320, 1, 0.3],
...               index=midx)
>>> s
lama    speed      45.0
        weight    200.0
        length      1.2
cow     speed      30.0
        weight    250.0
        length      1.5
falcon  speed     320.0
        weight      1.0
        length      0.3
dtype: float64
```

```
>>> s.drop(labels='weight', level=1)
lama    speed      45.0
        length      1.2
cow     speed      30.0
        length      1.5
falcon  speed     320.0
        length      0.3
dtype: float64
```

pandas.Series.drop_duplicates

`Series.drop_duplicates(keep='first', inplace=False)`

Return Series with duplicate values removed.

Parameters

keep [{'first', 'last', `False`}, default 'first'] Method to handle dropping duplicates:

- 'first' : Drop duplicates except for the first occurrence.
- 'last' : Drop duplicates except for the last occurrence.
- `False` : Drop all duplicates.

inplace [bool, default `False`] If `True`, performs operation inplace and returns None.

Returns

Series or None Series with duplicates dropped or None if `inplace=True`.

See also:

Index.drop_duplicates Equivalent method on Index.

DataFrame.drop_duplicates Equivalent method on DataFrame.

Series.duplicated Related method on Series, indicating duplicate Series values.

Examples

Generate a Series with duplicated entries.

```
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'],
...               name='animal')
>>> s
0      lama
1       cow
2      lama
3    beetle
4      lama
5     hippo
Name: animal, dtype: object
```

With the 'keep' parameter, the selection behaviour of duplicated values can be changed. The value 'first' keeps the first occurrence for each set of duplicated entries. The default value of keep is 'first'.

```
>>> s.drop_duplicates()
0      lama
1       cow
3    beetle
5     hippo
Name: animal, dtype: object
```

The value 'last' for parameter 'keep' keeps the last occurrence for each set of duplicated entries.

```
>>> s.drop_duplicates(keep='last')
1       cow
3    beetle
4      lama
```

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```
5     hippo
Name: animal, dtype: object
```

The value `False` for parameter 'keep' discards all sets of duplicated entries. Setting the value of 'inplace' to `True` performs the operation inplace and returns `None`.

```
>>> s.drop_duplicates(keep=False, inplace=True)
>>> s
1       cow
3    beetle
5     hippo
Name: animal, dtype: object
```

pandas.Series.droplevel

`Series.`**`droplevel`**(*level*, *axis=0*)

Return DataFrame with requested index / column level(s) removed.

New in version 0.24.0.

Parameters

level [int, str, or list-like] If a string is given, must be the name of a level If list-like, elements must be names or positional indexes of levels.

axis [{0 or 'index', 1 or 'columns'}, default 0] Axis along which the level(s) is removed:

- 0 or 'index': remove level(s) in column.
- 1 or 'columns': remove level(s) in row.

Returns

DataFrame DataFrame with requested index / column level(s) removed.

Examples

```
>>> df = pd.DataFrame([
...     [1, 2, 3, 4],
...     [5, 6, 7, 8],
...     [9, 10, 11, 12]
... ]).set_index([0, 1]).rename_axis(['a', 'b'])
```

```
>>> df.columns = pd.MultiIndex.from_tuples([
...     ('c', 'e'), ('d', 'f')
... ], names=['level_1', 'level_2'])
```

```
>>> df
level_1   c   d
level_2   e   f
a b
1 2       3   4
5 6       7   8
9 10     11  12
```

```
>>> df.droplevel('a')
level_1   c   d
level_2   e   f
b
2         3   4
6         7   8
10       11  12
```

```
>>> df.droplevel('level_2', axis=1)
level_1   c   d
a b
1 2       3   4
5 6       7   8
9 10     11  12
```

pandas.Series.dropna

Series.**dropna**(*axis=0*, *inplace=False*, *how=None*)

Return a new Series with missing values removed.

See the *User Guide* for more on which values are considered missing, and how to work with missing data.

Parameters

axis [{0 or 'index'}, default 0] There is only one axis to drop values from.

inplace [bool, default False] If True, do operation inplace and return None.

how [str, optional] Not in use. Kept for compatibility.

Returns

Series or None Series with NA entries dropped from it or None if `inplace=True`.

See also:

Series.isna Indicate missing values.

Series.notna Indicate existing (non-missing) values.

Series.fillna Replace missing values.

DataFrame.dropna Drop rows or columns which contain NA values.

Index.dropna Drop missing indices.

Examples

```
>>> ser = pd.Series([1., 2., np.nan])
>>> ser
0    1.0
1    2.0
2    NaN
dtype: float64
```

Drop NA values from a Series.

```
>>> ser.dropna()
0    1.0
1    2.0
dtype: float64
```

Keep the Series with valid entries in the same variable.

```
>>> ser.dropna(inplace=True)
>>> ser
0    1.0
1    2.0
dtype: float64
```

Empty strings are not considered NA values. `None` is considered an NA value.

```
>>> ser = pd.Series([np.NaN, 2, pd.NaT, '', None, 'I stay'])
>>> ser
0       NaN
1         2
2       NaT
3
4      None
5    I stay
dtype: object
>>> ser.dropna()
1         2
3
5    I stay
dtype: object
```

pandas.Series.dt

`Series.dt()`

Accessor object for datetimelike properties of the Series values.

Examples

```
>>> seconds_series = pd.Series(pd.date_range("2000-01-01", periods=3, freq="s
↪"))
>>> seconds_series
0   2000-01-01 00:00:00
1   2000-01-01 00:00:01
2   2000-01-01 00:00:02
dtype: datetime64[ns]
>>> seconds_series.dt.second
0    0
1    1
2    2
dtype: int64
```

```
>>> hours_series = pd.Series(pd.date_range("2000-01-01", periods=3, freq="h
↪"))
>>> hours_series
```

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```
0   2000-01-01 00:00:00
1   2000-01-01 01:00:00
2   2000-01-01 02:00:00
dtype: datetime64[ns]
>>> hours_series.dt.hour
0    0
1    1
2    2
dtype: int64
```

```
>>> quarters_series = pd.Series(pd.date_range("2000-01-01", periods=3, freq=
↪"q"))
>>> quarters_series
0   2000-03-31
1   2000-06-30
2   2000-09-30
dtype: datetime64[ns]
>>> quarters_series.dt.quarter
0    1
1    2
2    3
dtype: int64
```

Returns a Series indexed like the original Series. Raises TypeError if the Series does not contain datetimelike values.

pandas.Series.duplicated

Series.**duplicated**(*keep='first'*)

Indicate duplicate Series values.

Duplicated values are indicated as `True` values in the resulting Series. Either all duplicates, all except the first or all except the last occurrence of duplicates can be indicated.

Parameters

keep [{'first', 'last', False}, default 'first'] Method to handle dropping duplicates:

- 'first' : Mark duplicates as `True` except for the first occurrence.
- 'last' : Mark duplicates as `True` except for the last occurrence.
- `False` : Mark all duplicates as `True`.

Returns

Series Series indicating whether each value has occurred in the preceding values.

See also:

Index.duplicated Equivalent method on pandas.Index.

DataFrame.duplicated Equivalent method on pandas.DataFrame.

Series.drop_duplicates Remove duplicate values from Series.

Examples

By default, for each set of duplicated values, the first occurrence is set on False and all others on True:

```
>>> animals = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> animals.duplicated()
0    False
1    False
2     True
3    False
4     True
dtype: bool
```

which is equivalent to

```
>>> animals.duplicated(keep='first')
0    False
1    False
2     True
3    False
4     True
dtype: bool
```

By using 'last', the last occurrence of each set of duplicated values is set on False and all others on True:

```
>>> animals.duplicated(keep='last')
0     True
1    False
2     True
3    False
4    False
dtype: bool
```

By setting keep on `False`, all duplicates are True:

```
>>> animals.duplicated(keep=False)
0     True
1    False
2     True
3    False
4     True
dtype: bool
```

pandas.Series.eq

`Series.`**`eq`**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Equal to of series and other, element-wise (binary operator *eq*).

Equivalent to `series == other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before

computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.eq(b, fill_value=0)
a     True
b    False
c    False
d    False
e    False
dtype: bool
```

pandas.Series.equals

Series.**equals**(*other*)

Test whether two objects contain the same elements.

This function allows two Series or DataFrames to be compared against each other to see if they have the same shape and elements. NaNs in the same location are considered equal.

The row/column index do not need to have the same type, as long as the values are considered equal. Corresponding columns must be of the same dtype.

Parameters

other [Series or DataFrame] The other Series or DataFrame to be compared with the first.

Returns

bool True if all elements are the same in both objects, False otherwise.

See also:

Series.eq Compare two Series objects of the same length and return a Series where each element is True if the element in each Series is equal, False otherwise.

DataFrame.eq Compare two DataFrame objects of the same shape and return a DataFrame where each element is True if the respective element in each DataFrame is equal, False otherwise.

testing.assert_series_equal Raises an AssertionError if left and right are not equal. Provides an easy interface to ignore inequality in dtypes, indexes and precision among others.

testing.assert_frame_equal Like assert_series_equal, but targets DataFrames.

numpy.array_equal Return True if two arrays have the same shape and elements, False otherwise.

Examples

```
>>> df = pd.DataFrame({1: [10], 2: [20]})
>>> df
    1   2
0  10  20
```

DataFrames df and exactly_equal have the same types and values for their elements and column labels, which will return True.

```
>>> exactly_equal = pd.DataFrame({1: [10], 2: [20]})
>>> exactly_equal
    1   2
0  10  20
>>> df.equals(exactly_equal)
True
```

DataFrames df and different_column_type have the same element types and values, but have different types for the column labels, which will still return True.

```
>>> different_column_type = pd.DataFrame({1.0: [10], 2.0: [20]})
>>> different_column_type
   1.0  2.0
0   10   20
>>> df.equals(different_column_type)
True
```

DataFrames df and different_data_type have different types for the same values for their elements, and will return False even though their column labels are the same values and types.

```
>>> different_data_type = pd.DataFrame({1: [10.0], 2: [20.0]})
>>> different_data_type
      1     2
0  10.0  20.0
>>> df.equals(different_data_type)
False
```

pandas.Series.ewm

Series.**ewm**(*com=None*, *span=None*, *halflife=None*, *alpha=None*, *min_periods=0*, *adjust=True*, *ignore_na=False*, *axis=0*, *times=None*)

Provide exponential weighted (EW) functions.

Available EW functions: `mean()`, `var()`, `std()`, `corr()`, `cov()`.

Exactly one parameter: `com`, `span`, `halflife`, or `alpha` must be provided.

Parameters

com [float, optional] Specify decay in terms of center of mass, $\alpha = 1/(1 + com)$, for $com \geq 0$.

span [float, optional] Specify decay in terms of span, $\alpha = 2/(span + 1)$, for $span \geq 1$.

halflife [float, str, timedelta, optional] Specify decay in terms of half-life, $\alpha = 1 - \exp(-\ln(2)/halflife)$, for $halflife > 0$.

If `times` is specified, the time unit (str or timedelta) over which an observation decays to half its value. Only applicable to `mean()` and halflife value will not apply to the other functions.

New in version 1.1.0.

alpha [float, optional] Specify smoothing factor α directly, $0 < \alpha \leq 1$.

min_periods [int, default 0] Minimum number of observations in window required to have a value (otherwise result is NA).

adjust [bool, default True] Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average).

- When `adjust=True` (default), the EW function is calculated using weights $w_i = (1 - \alpha)^i$. For example, the EW moving average of the series $[x_0, x_1, ..., x_t]$ would be:

$$y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2 x_{t-2} + ... + (1 - \alpha)^t x_0}{1 + (1 - \alpha) + (1 - \alpha)^2 + ... + (1 - \alpha)^t}$$

- When `adjust=False`, the exponentially weighted function is calculated recursively:

$$y_0 = x_0$$
$$y_t = (1 - \alpha)y_{t-1} + \alpha x_t,$$

ignore_na [bool, default False] Ignore missing values when calculating weights; specify `True` to reproduce pre-0.15.0 behavior.

- When `ignore_na=False` (default), weights are based on absolute positions. For example, the weights of x_0 and x_2 used in calculating the final weighted average of [x_0, None, x_2] are $(1 - \alpha)^2$ and 1 if `adjust=True`, and $(1 - \alpha)^2$ and α if `adjust=False`.

- When `ignore_na=True` (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x_0 and x_2 used in calculating the final weighted average of [x_0, None, x_2] are $1 - \alpha$ and 1 if `adjust=True`, and $1 - \alpha$ and α if `adjust=False`.

axis [{0, 1}, default 0] The axis to use. The value 0 identifies the rows, and 1 identifies the columns.

times [str, np.ndarray, Series, default None] New in version 1.1.0.

Times corresponding to the observations. Must be monotonically increasing and `datetime64[ns]` dtype.

If str, the name of the column in the DataFrame representing the times.

If 1-D array like, a sequence with the same shape as the observations.

Only applicable to `mean()`.

Returns

DataFrame A Window sub-classed for the particular operation.

See also:

rolling Provides rolling window calculations.

expanding Provides expanding transformations.

Notes

More details can be found at: *Exponentially weighted windows*.

Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

```
>>> df.ewm(com=0.5).mean()
          B
0  0.000000
1  0.750000
2  1.615385
3  1.615385
4  3.670213
```

Specifying `times` with a timedelta `halflife` when computing mean.

```
>>> times = ['2020-01-01', '2020-01-03', '2020-01-10', '2020-01-15', '2020-
↪01-17']
>>> df.ewm(halflife='4 days', times=pd.DatetimeIndex(times)).mean()
          B
0  0.000000
1  0.585786
2  1.523889
3  1.523889
4  3.233686
```

pandas.Series.expanding

Series.**expanding**(*min_periods=1*, *center=None*, *axis=0*)

Provide expanding transformations.

Parameters

min_periods [int, default 1] Minimum number of observations in window required to have a value (otherwise result is NA).

center [bool, default False] Set the labels at the center of the window.

axis [int or str, default 0]

Returns

a Window sub-classed for the particular operation

See also:

rolling Provides rolling window calculations.

ewm Provides exponential weighted functions.

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

Examples

```
>>> df = pd.DataFrame({"B": [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

```
>>> df.expanding(2).sum()
     B
0  NaN
1  1.0
2  3.0
3  3.0
4  7.0
```

pandas.Series.explode

Series.**explode**(*ignore_index=False*)

Transform each element of a list-like to a row.

New in version 0.25.0.

Parameters

ignore_index [bool, default False] If True, the resulting index will be labeled 0, 1, . . . , n - 1.

New in version 1.1.0.

Returns

Series Exploded lists to rows; index will be duplicated for these rows.

See also:

Series.str.split Split string values on specified separator.

Series.unstack Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame.

DataFrame.melt Unpivot a DataFrame from wide format to long format.

DataFrame.explode Explode a DataFrame from list-like columns to long format.

Notes

This routine will explode list-likes including lists, tuples, sets, Series, and np.ndarray. The result dtype of the subset rows will be object. Scalars will be returned unchanged, and empty list-likes will result in a np.nan for that row. In addition, the ordering of elements in the output will be non-deterministic when exploding sets.

Examples

```
>>> s = pd.Series([[1, 2, 3], 'foo', [], [3, 4]])
>>> s
0    [1, 2, 3]
1          foo
2           []
3       [3, 4]
dtype: object
```

```
>>> s.explode()
0      1
0      2
0      3
1    foo
2    NaN
3      3
3      4
dtype: object
```

pandas.Series.factorize

Series.**factorize**(*sort=False*, *na_sentinel=- 1*)

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. *factorize* is available as both a top-level function *pandas.factorize()*, and as a method *Series.factorize()* and *Index.factorize()*.

Parameters

sort [bool, default False] Sort *uniques* and shuffle *codes* to maintain the relationship.

na_sentinel [int or None, default -1] Value to mark "not found". If None, will not drop the NaN from the uniques of the values.

Changed in version 1.1.2.

Returns

codes [ndarray] An integer ndarray that's an indexer into *uniques*. `uniques.take(codes)` will have the same values as *values*.

uniques [ndarray, Index, or Categorical] The unique valid values. When *values* is Categorical, *uniques* is a Categorical. When *values* is some other pandas object, an *Index* is returned. Otherwise, a 1-D ndarray is returned.

Note: Even if there's a missing value in *values*, *uniques* will *not* contain an entry for it.

See also:

cut Discretize continuous-valued array.

unique Find the unique value in an array.

Examples

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like *Series.factorize()*.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the *uniques* will be sorted, and *codes* will be shuffled so that the relationship is the maintained.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1]...)
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in *codes* with *na_sentinel* (`-1` by default). Note that missing values are never included in *uniques*.

```
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1,  1,  2,  0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we've only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of *uniques* will differ. For Categoricals, a *Categorical* is returned.

```
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
['a', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Notice that `'b'` is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
Index(['a', 'c'], dtype='object')
```

If NaN is in the values, and we want to include NaN in the uniques of the values, it can be achieved by setting `na_sentinel=None`.

```
>>> values = np.array([1, 2, 1, np.nan])
>>> codes, uniques = pd.factorize(values)  # default: na_sentinel=-1
>>> codes
array([ 0,  1,  0, -1])
>>> uniques
array([1., 2.])
```

```
>>> codes, uniques = pd.factorize(values, na_sentinel=None)
>>> codes
array([0, 1, 0, 2])
>>> uniques
array([ 1.,  2., nan])
```

pandas.Series.ffill

`Series.`**`ffill`**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *`DataFrame.fillna()`* with `method='ffill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.Series.fillna

Series.**fillna**(*value=None*, *method=None*, *axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Fill NA/NaN values using the specified method.

Parameters

value [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

method [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use next valid observation to fill gap.

axis [{0 or 'index'}] Axis along which to fill missing values.

inplace [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

downcast [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

Returns

Series or None Object with missing values filled or None if `inplace=True`.

See also:

interpolate Fill NaN values using interpolation.

reindex Conform object to new index.

asfreq Convert TimeSeries to specified frequency.

Examples

```
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                    [3, 4, np.nan, 1],
...                    [np.nan, np.nan, np.nan, 5],
...                    [np.nan, 3, np.nan, 4]],
...                   columns=list('ABCD'))
>>> df
     A    B   C  D
0  NaN  2.0 NaN  0
1  3.0  4.0 NaN  1
2  NaN  NaN NaN  5
3  NaN  3.0 NaN  4
```

Replace all NaN elements with 0s.

```
>>> df.fillna(0)
    A   B   C   D
0   0.0 2.0 0.0 0
1   3.0 4.0 0.0 1
2   0.0 0.0 0.0 5
3   0.0 3.0 0.0 4
```

We can also propagate non-null values forward or backward.

```
>>> df.fillna(method='ffill')
    A   B   C   D
0   NaN 2.0 NaN 0
1   3.0 4.0 NaN 1
2   3.0 4.0 NaN 5
3   3.0 3.0 NaN 4
```

Replace all NaN elements in column 'A', 'B', 'C', and 'D', with 0, 1, 2, and 3 respectively.

```
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
    A   B   C   D
0   0.0 2.0 2.0 0
1   3.0 4.0 2.0 1
2   0.0 1.0 2.0 5
3   0.0 3.0 2.0 4
```

Only replace the first NaN element.

```
>>> df.fillna(value=values, limit=1)
    A   B   C   D
0   0.0 2.0 2.0 0
1   3.0 4.0 NaN 1
2   NaN 1.0 NaN 5
3   NaN 3.0 NaN 4
```

pandas.Series.filter

Series.**filter**(*items=None*, *like=None*, *regex=None*, *axis=None*)

Subset the dataframe rows or columns according to the specified index labels.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

Parameters

items [list-like] Keep labels from axis which are in items.

like [str] Keep labels from axis for which "like in label == True".

regex [str (regular expression)] Keep labels from axis for which re.search(regex, label) == True.

axis [{0 or 'index', 1 or 'columns', None}, default None] The axis to filter on, expressed either as an index (int) or axis name (str). By default this is the info axis, 'index' for Series, 'columns' for DataFrame.

Returns

same type as input object

See also:

DataFrame.loc Access a group of rows and columns by label(s) or a boolean array.

Notes

The `items`, `like`, and `regex` parameters are enforced to be mutually exclusive.

`axis` defaults to the info axis that is used when indexing with `[]`.

Examples

```
>>> df = pd.DataFrame(np.array(([1, 2, 3], [4, 5, 6])),
...                   index=['mouse', 'rabbit'],
...                   columns=['one', 'two', 'three'])
>>> df
        one  two  three
mouse     1    2      3
rabbit    4    5      6
```

```
>>> # select columns by name
>>> df.filter(items=['one', 'three'])
         one  three
mouse     1      3
rabbit    4      6
```

```
>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
         one  three
mouse     1      3
rabbit    4      6
```

```
>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
         one  two  three
rabbit    4    5      6
```

pandas.Series.first

`Series.`**`first`**(*offset*)

Select initial periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the first few rows based on a date offset.

Parameters

offset [str, DateOffset or dateutil.relativedelta] The offset length of the data that will be selected. For instance, '1M' will display all the rows having their index within the first month.

Returns

Series or DataFrame A subset of the caller.

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

last Select final periods of time series based on a date offset.

at_time Select values at a particular time of the day.

between_time Select values between particular times of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
            A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the first 3 days:

```
>>> ts.first('3D')
            A
2018-04-09  1
2018-04-11  2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

pandas.Series.first_valid_index

Series.**first_valid_index**()

Return index for first non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

pandas.Series.floordiv

Series.**floordiv**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Integer division of series and other, element-wise (binary operator *floordiv*).

Equivalent to `series // other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rfloordiv Reverse of the Integer division operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.floordiv(b, fill_value=0)
a    1.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

pandas.Series.ge

Series.**ge**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Greater than or equal to of series and other, element-wise (binary operator *ge*).

Equivalent to `series >= other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
e    1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a    0.0
b    1.0
c    2.0
d    NaN
f    1.0
dtype: float64
>>> a.ge(b, fill_value=0)
a     True
b     True
c    False
d    False
e     True
f    False
dtype: bool
```

pandas.Series.get

Series.**get**(*key*, *default=None*)

Get item from object for given key (ex: DataFrame column).

Returns default value if not found.

Parameters

key [object]

Returns

value [same type as items contained in object]

pandas.Series.groupby

Series.**groupby**(*by=None*, *axis=0*, *level=None*, *as_index=True*, *sort=True*, *group_keys=True*, *squeeze=<object object>*, *observed=False*, *dropna=True*)

Group Series using a mapper or by a Series of columns.

A groupby operation involves some combination of splitting the object, applying a function, and combining the results. This can be used to group large amounts of data and compute operations on these groups.

Parameters

by [mapping, function, label, or list of labels] Used to determine the groups for the groupby. If `by` is a function, it's called on each value of the object's index. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups (the Series' values are first aligned; see `.align()` method). If an ndarray is passed, the values are used as-is to determine the groups. A label or list of labels may be passed to group by the columns in `self`. Notice that a tuple is interpreted as a (single) key.

axis [{0 or 'index', 1 or 'columns'}, default 0] Split along rows (0) or columns (1).

level [int, level name, or sequence of such, default None] If the axis is a MultiIndex (hierarchical), group by a particular level or levels.

as_index [bool, default True] For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively "SQL-style" grouped output.

sort [bool, default True] Sort group keys. Get better performance by turning this off. Note this does not influence the order of observations within each group. Groupby preserves the order of rows within each group.

group_keys [bool, default True] When calling apply, add group keys to index to identify pieces.

squeeze [bool, default False] Reduce the dimensionality of the return type if possible, otherwise return a consistent type.

Deprecated since version 1.1.0.

observed [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

dropna [bool, default True] If True, and if group keys contain NA values, NA values together with row/column will be dropped. If False, NA values will also be treated as the key in groups

New in version 1.1.0.

Returns

SeriesGroupBy Returns a groupby object that contains information about the groups.

See also:

resample Convenience method for frequency conversion and resampling of time series.

Notes

See the user guide for more.

Examples

```
>>> ser = pd.Series([390., 350., 30., 20.],
...                 index=['Falcon', 'Falcon', 'Parrot', 'Parrot'], name=
↪"Max Speed")
>>> ser
Falcon    390.0
Falcon    350.0
Parrot     30.0
Parrot     20.0
Name: Max Speed, dtype: float64
>>> ser.groupby(["a", "b", "a", "b"]).mean()
a    210.0
b    185.0
Name: Max Speed, dtype: float64
>>> ser.groupby(level=0).mean()
Falcon    370.0
Parrot     25.0
Name: Max Speed, dtype: float64
>>> ser.groupby(ser > 100).mean()
Max Speed
False     25.0
True     370.0
Name: Max Speed, dtype: float64
```

Grouping by Indexes

We can groupby different levels of a hierarchical index using the *level* parameter:

```
>>> arrays = [['Falcon', 'Falcon', 'Parrot', 'Parrot'],
...           ['Captive', 'Wild', 'Captive', 'Wild']]
>>> index = pd.MultiIndex.from_arrays(arrays, names=('Animal', 'Type'))
>>> ser = pd.Series([390., 350., 30., 20.], index=index, name="Max Speed")
>>> ser
Animal  Type
Falcon  Captive    390.0
        Wild       350.0
Parrot  Captive     30.0
        Wild        20.0
```

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```
Name: Max Speed, dtype: float64
>>> ser.groupby(level=0).mean()
Animal
Falcon    370.0
Parrot     25.0
Name: Max Speed, dtype: float64
>>> ser.groupby(level="Type").mean()
Type
Captive    210.0
Wild       185.0
Name: Max Speed, dtype: float64
```

We can also choose to include *NA* in group keys or not by defining *dropna* parameter, the default setting is *True*:

```
>>> ser = pd.Series([1, 2, 3, 3], index=["a", 'a', 'b', np.nan])
>>> ser.groupby(level=0).sum()
a    3
b    3
dtype: int64
```

```
>>> ser.groupby(level=0, dropna=False).sum()
a    3
b    3
NaN  3
dtype: int64
```

```
>>> arrays = ['Falcon', 'Falcon', 'Parrot', 'Parrot']
>>> ser = pd.Series([390., 350., 30., 20.], index=arrays, name="Max Speed")
>>> ser.groupby(["a", "b", "a", np.nan]).mean()
a    210.0
b    350.0
Name: Max Speed, dtype: float64
```

```
>>> ser.groupby(["a", "b", "a", np.nan], dropna=False).mean()
a    210.0
b    350.0
NaN   20.0
Name: Max Speed, dtype: float64
```

pandas.Series.gt

`Series.gt`(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Greater than of series and other, element-wise (binary operator *gt*).

Equivalent to `series > other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before

computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
e    1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a    0.0
b    1.0
c    2.0
d    NaN
f    1.0
dtype: float64
>>> a.gt(b, fill_value=0)
a     True
b    False
c    False
d    False
e     True
f    False
dtype: bool
```

pandas.Series.head

`Series.head(n=5)`

Return the first *n* rows.

This function returns the first *n* rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

For negative values of *n*, this function returns all rows except the last *n* rows, equivalent to `df[:-n]`.

Parameters

n [int, default 5] Number of rows to select.

Returns

same type as caller The first *n* rows of the caller object.

See also:

DataFrame.tail Returns the last *n* rows.

Examples

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                               'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
5     parrot
6      shark
7      whale
8      zebra
```

Viewing the first 5 lines

```
>>> df.head()
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
```

Viewing the first *n* lines (three in this case)

```
>>> df.head(3)
      animal
0  alligator
1        bee
2     falcon
```

For negative values of *n*

```
>>> df.head(-3)
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
5     parrot
```

pandas.Series.hist

Series.**hist**(*by=None*, *ax=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *figsize=None*, *bins=10*, *backend=None*, *legend=False*, ***kwargs*)

Draw histogram of the input series using matplotlib.

Parameters

by [object, optional] If passed, then used to form histograms for separate groups.

ax [matplotlib axis object] If not passed, uses gca().

grid [bool, default True] Whether to show axis grid lines.

xlabelsize [int, default None] If specified changes the x-axis label size.

xrot [float, default None] Rotation of x axis labels.

ylabelsize [int, default None] If specified changes the y-axis label size.

yrot [float, default None] Rotation of y axis labels.

figsize [tuple, default None] Figure size in inches by default.

bins [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

legend [bool, default False] Whether to show the legend.

New in version 1.1.0.

****kwargs** To be passed to the actual plotting function.

Returns

matplotlib.AxesSubplot A histogram plot.

See also:

`matplotlib.axes.Axes.hist` Plot a histogram using matplotlib.

pandas.Series.idxmax

`Series.`**`idxmax`**(*axis=0*, *skipna=True*, **args*, ***kwargs*)

Return the row label of the maximum value.

If multiple values equal the maximum, the first row label with that value is returned.

Parameters

axis [int, default 0] For compatibility with DataFrame.idxmax. Redundant for application on Series.

skipna [bool, default True] Exclude NA/null values. If the entire Series is NA, the result will be NA.

***args, ****kwargs** Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Index Label of the maximum value.

Raises

ValueError If the Series is empty.

See also:

numpy.argmax Return indices of the maximum values along the given axis.

DataFrame.idxmax Return index of first occurrence of maximum over requested axis.

Series.idxmin Return index *label* of the first occurrence of minimum of values.

Notes

This method is the Series version of `ndarray.argmax`. This method returns the label of the maximum, while `ndarray.argmax` returns the position. To get the position, use `series.values.argmax()`.

Examples

```
>>> s = pd.Series(data=[1, None, 4, 3, 4],
...               index=['A', 'B', 'C', 'D', 'E'])
>>> s
A    1.0
B    NaN
C    4.0
D    3.0
E    4.0
dtype: float64
```

```
>>> s.idxmax()
'C'
```

If *skipna* is False and there is an NA value in the data, the function returns `nan`.

```
>>> s.idxmax(skipna=False)
nan
```

pandas.Series.idxmin

`Series.`**`idxmin`**(*axis=0*, *skipna=True*, **args*, ***kwargs*)

Return the row label of the minimum value.

If multiple values equal the minimum, the first row label with that value is returned.

Parameters

axis [int, default 0] For compatibility with DataFrame.idxmin. Redundant for application on Series.

skipna [bool, default True] Exclude NA/null values. If the entire Series is NA, the result will be NA.

***args, **kwargs** Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Index Label of the minimum value.

Raises

ValueError If the Series is empty.

See also:

numpy.argmin Return indices of the minimum values along the given axis.

DataFrame.idxmin Return index of first occurrence of minimum over requested axis.

Series.idxmax Return index *label* of the first occurrence of maximum of values.

Notes

This method is the Series version of `ndarray.argmin`. This method returns the label of the minimum, while `ndarray.argmin` returns the position. To get the position, use `series.values.argmin()`.

Examples

```
>>> s = pd.Series(data=[1, None, 4, 1],
...               index=['A', 'B', 'C', 'D'])
>>> s
A    1.0
B    NaN
C    4.0
D    1.0
dtype: float64
```

```
>>> s.idxmin()
'A'
```

If *skipna* is False and there is an NA value in the data, the function returns `nan`.

```
>>> s.idxmin(skipna=False)
nan
```

pandas.Series.infer_objects

`Series.`**`infer_objects`**`()`

Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

Returns

converted [same type as input object]

See also:

to_datetime Convert argument to datetime.

to_timedelta Convert argument to timedelta.

to_numeric Convert argument to numeric type.

convert_dtypes Convert argument to best possible dtype.

Examples

```
>>> df = pd.DataFrame({"A": ["a", 1, 2, 3]})
>>> df = df.iloc[1:]
>>> df
   A
1  1
2  2
3  3
```

```
>>> df.dtypes
A    object
dtype: object
```

```
>>> df.infer_objects().dtypes
A    int64
dtype: object
```

pandas.Series.interpolate

Series.**interpolate**(*method='linear'*, *axis=0*, *limit=None*, *inplace=False*, *limit_direction=None*, *limit_area=None*, *downcast=None*, ***kwargs*)

Fill NaN values using an interpolation method.

Please note that only `method='linear'` is supported for DataFrame/Series with a MultiIndex.

Parameters

method [str, default 'linear'] Interpolation technique to use. One of:

- 'linear': Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
- 'time': Works on daily and higher resolution data to interpolate given length of interval.
- 'index', 'values': use the actual numerical values of the index.
- 'pad': Fill in NaNs using existing values.
- 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'spline', 'barycentric', 'polynomial': Passed to *scipy.interpolate.interp1d*. These methods use the numerical values of the index. Both 'polynomial' and 'spline' require that you also specify an *order* (int), e.g. `df.interpolate(method='polynomial', order=5)`.
- 'krogh', 'piecewise_polynomial', 'spline', 'pchip', 'akima', 'cubicspline': Wrappers around the SciPy interpolation methods of similar names. See *Notes*.
- 'from_derivatives': Refers to *scipy.interpolate.BPoly.from_derivatives* which replaces 'piecewise_polynomial' interpolation method in scipy 0.18.

axis [{{0 or 'index', 1 or 'columns', None}}, default None] Axis to interpolate along.

limit [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

inplace [bool, default False] Update the data in place if possible.

limit_direction [{{'forward', 'backward', 'both'}}, Optional] Consecutive NaNs will be filled in this direction.

If limit is specified:

- If 'method' is 'pad' or 'ffill', 'limit_direction' must be 'forward'.
- If 'method' is 'backfill' or 'bfill', 'limit_direction' must be 'backwards'.

If 'limit' is not specified:

- If 'method' is 'backfill' or 'bfill', the default is 'backward'
- else the default is 'forward'

Changed in version 1.1.0: raises ValueError if *limit_direction* is 'forward' or 'both' and method is 'backfill' or 'bfill'. raises ValueError if *limit_direction* is 'backward' or 'both' and method is 'pad' or 'ffill'.

limit_area [{{*None*, 'inside', 'outside'}}, default None] If limit is specified, consecutive NaNs will be filled with this restriction.

- `None`: No fill restriction.
- 'inside': Only fill NaNs surrounded by valid values (interpolate).
- 'outside': Only fill NaNs outside valid values (extrapolate).

downcast [optional, 'infer' or None, defaults to None] Downcast dtypes if possible.

``****kwargs``** [optional] Keyword arguments to pass on to the interpolating function.

Returns

Series or DataFrame or None Returns the same object type as the caller, interpolated at some or all `NaN` values or None if `inplace=True`.

See also:

fillna Fill missing values using different methods.

scipy.interpolate.Akima1DInterpolator Piecewise cubic polynomials (Akima interpolator).

scipy.interpolate.BPoly.from_derivatives Piecewise polynomial in the Bernstein basis.

scipy.interpolate.interp1d Interpolate a 1-D function.

scipy.interpolate.KroghInterpolator Interpolate polynomial (Krogh interpolator).

scipy.interpolate.PchipInterpolator PCHIP 1-d monotonic cubic interpolation.

scipy.interpolate.CubicSpline Cubic spline data interpolator.

Notes

The 'krogh', 'piecewise_polynomial', 'spline', 'pchip' and 'akima' methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the SciPy documentation and SciPy tutorial.

Examples

Filling in `NaN` in a *`Series`* via linear interpolation.

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0    0.0
1    1.0
2    NaN
3    3.0
dtype: float64
>>> s.interpolate()
0    0.0
1    1.0
2    2.0
3    3.0
dtype: float64
```

Filling in `NaN` in a Series by padding, but filling at most two consecutive `NaN` at a time.

```
>>> s = pd.Series([np.nan, "single_one", np.nan,
...                "fill_two_more", np.nan, np.nan, np.nan,
...                4.71, np.nan])
>>> s
0              NaN
1       single_one
2              NaN
3    fill_two_more
4              NaN
5              NaN
6              NaN
7             4.71
8              NaN
dtype: object
>>> s.interpolate(method='pad', limit=2)
0              NaN
1       single_one
2       single_one
3    fill_two_more
4    fill_two_more
5    fill_two_more
6              NaN
7             4.71
8             4.71
dtype: object
```

Filling in `NaN` in a Series via polynomial interpolation or splines: Both 'polynomial' and 'spline' methods require that you also specify an `order` (int).

```
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0    0.000000
1    2.000000
2    4.666667
3    8.000000
dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column 'a' is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column 'b' remains NaN, because there is no entry before it to use for interpolation.

```
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                    (np.nan, 2.0, np.nan, np.nan),
...                    (2.0, 3.0, np.nan, 9.0),
...                    (np.nan, 4.0, -4.0, 16.0)],
...                   columns=list('abcd'))
>>> df
     a    b    c     d
0  0.0  NaN -1.0   1.0
1  NaN  2.0  NaN   NaN
2  2.0  3.0  NaN   9.0
3  NaN  4.0 -4.0  16.0
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
     a    b    c     d
0  0.0  NaN -1.0   1.0
1  1.0  2.0 -2.0   5.0
2  2.0  3.0 -3.0   9.0
3  2.0  4.0 -4.0  16.0
```

Using polynomial interpolation.

```
>>> df['d'].interpolate(method='polynomial', order=2)
0     1.0
1     4.0
2     9.0
3    16.0
Name: d, dtype: float64
```

pandas.Series.isin

Series.**isin**(*values*)

Whether elements in Series are contained in *values*.

Return a boolean Series showing whether each element in the Series matches an element in the passed sequence of *values* exactly.

Parameters

values [set or list-like] The sequence of values to test. Passing in a single string will raise a TypeError. Instead, turn a single string into a list of one element.

Returns

Series Series of booleans indicating if each element is in values.

Raises

TypeError

- If *values* is a string

See also:

DataFrame.isin Equivalent method on DataFrame.

Examples

```
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama',
...                'hippo'], name='animal')
>>> s.isin(['cow', 'lama'])
0     True
1     True
2     True
3    False
4     True
5    False
Name: animal, dtype: bool
```

Passing a single string as `s.isin('lama')` will raise an error. Use a list of one element instead:

```
>>> s.isin(['lama'])
0     True
1    False
2     True
3    False
4     True
5    False
Name: animal, dtype: bool
```

Strings and integers are distinct and are therefore not comparable:

```
>>> pd.Series([1]).isin(['1'])
0    False
dtype: bool
>>> pd.Series([1.1]).isin(['1.1'])
0    False
dtype: bool
```

pandas.Series.isna

Series.**isna**()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or `numpy.NaN`, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

Returns

Series Mask of bool values for each element in Series that indicates whether an element is an NA value.

See also:

Series.isnull Alias of isna.

Series.notna Boolean inverse of isna.

Series.dropna Omit axes labels with missing values.

isna Top-level isna.

Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.isna()
     age   born   name    toy
0  False   True  False   True
1  False  False  False  False
2   True  False  False  False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0    False
1    False
2     True
dtype: bool
```

pandas.Series.isnull

Series.**isnull**()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or `numpy.NaN`, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

Returns

Series Mask of bool values for each element in Series that indicates whether an element is an NA value.

See also:

Series.isnull Alias of isna.

Series.notna Boolean inverse of isna.

Series.dropna Omit axes labels with missing values.

isna Top-level isna.

Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.isna()
     age   born   name    toy
0  False   True  False   True
1  False  False  False  False
2   True  False  False  False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0    False
1    False
2     True
dtype: bool
```

pandas.Series.item

Series.**item**()

Return the first element of the underlying data as a Python scalar.

Returns

scalar The first element of %(klass)s.

Raises

ValueError If the data is not length-1.

pandas.Series.items

Series.**items**()

Lazily iterate over (index, value) tuples.

This method returns an iterable tuple (index, value). This is convenient if you want to create a lazy iterator.

Returns

iterable Iterable of tuples containing the (index, value) pairs from a Series.

See also:

DataFrame.items Iterate over (column name, Series) pairs.

DataFrame.iterrows Iterate over DataFrame rows as (index, Series) pairs.

Examples

```
>>> s = pd.Series(['A', 'B', 'C'])
>>> for index, value in s.items():
...     print(f"Index : {index}, Value : {value}")
Index : 0, Value : A
Index : 1, Value : B
Index : 2, Value : C
```

pandas.Series.iteritems

Series.**iteritems**()

Lazily iterate over (index, value) tuples.

This method returns an iterable tuple (index, value). This is convenient if you want to create a lazy iterator.

Returns

iterable Iterable of tuples containing the (index, value) pairs from a Series.

See also:

DataFrame.items Iterate over (column name, Series) pairs.

DataFrame.iterrows Iterate over DataFrame rows as (index, Series) pairs.

Examples

```
>>> s = pd.Series(['A', 'B', 'C'])
>>> for index, value in s.items():
...     print(f"Index : {index}, Value : {value}")
Index : 0, Value : A
Index : 1, Value : B
Index : 2, Value : C
```

pandas.Series.keys

Series.**keys**()

Return alias for index.

Returns

Index Index of the Series.

pandas.Series.kurt

Series.**kurt**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

pandas.Series.kurtosis

Series.**kurtosis**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

pandas.Series.last

Series.**last**(*offset*)

Select final periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the last few rows based on a date offset.

Parameters

offset [str, DateOffset, dateutil.relativedelta] The offset length of the data that will be selected. For instance, '3D' will display all the rows having their index within the last 3 days.

Returns

Series or DataFrame A subset of the caller.

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

first Select initial periods of time series based on a date offset.

at_time Select values at a particular time of the day.

between_time Select values between particular times of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
            A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the last 3 days:

```
>>> ts.last('3D')
            A
2018-04-13  3
2018-04-15  4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

pandas.Series.last_valid_index

Series.**last_valid_index**()

Return index for last non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

pandas.Series.le

Series.**le**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Less than or equal to of series and other, element-wise (binary operator *le*).

Equivalent to `series <= other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
e    1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a    0.0
b    1.0
c    2.0
d    NaN
f    1.0
dtype: float64
>>> a.le(b, fill_value=0)
```

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```
a    False
b     True
c     True
d    False
e    False
f     True
dtype: bool
```

pandas.Series.lt

Series.**lt**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Less than of series and other, element-wise (binary operator *lt*).

Equivalent to `series < other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
e    1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a    0.0
b    1.0
c    2.0
d    NaN
f    1.0
dtype: float64
>>> a.lt(b, fill_value=0)
a    False
b    False
c     True
d    False
```

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```
e    False
f     True
dtype: bool
```

pandas.Series.mad

Series.**mad**(*axis=None*, *skipna=None*, *level=None*)

Return the mean absolute deviation of the values over the requested axis.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default None] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

Returns

scalar or Series (if level specified)

pandas.Series.map

Series.**map**(*arg*, *na_action=None*)

Map values of Series according to input correspondence.

Used for substituting each value in a Series with another value, that may be derived from a function, a `dict` or a *Series*.

Parameters

arg [function, collections.abc.Mapping subclass or Series] Mapping correspondence.

na_action [{None, 'ignore'}, default None] If 'ignore', propagate NaN values, without passing them to the mapping correspondence.

Returns

Series Same index as caller.

See also:

Series.apply For applying more complex functions on a Series.

DataFrame.apply Apply a function row-/column-wise.

DataFrame.applymap Apply a function elementwise on a whole DataFrame.

Notes

When `arg` is a dictionary, values in Series that are not in the dictionary (as keys) are converted to `NaN`. However, if the dictionary is a `dict` subclass that defines `__missing__` (i.e. provides a method for default values), then this default is used rather than `NaN`.

Examples

```
>>> s = pd.Series(['cat', 'dog', np.nan, 'rabbit'])
>>> s
0      cat
1      dog
2      NaN
3   rabbit
dtype: object
```

`map` accepts a `dict` or a `Series`. Values that are not found in the `dict` are converted to `NaN`, unless the dict has a default value (e.g. `defaultdict`):

```
>>> s.map({'cat': 'kitten', 'dog': 'puppy'})
0   kitten
1    puppy
2      NaN
3      NaN
dtype: object
```

It also accepts a function:

```
>>> s.map('I am a {}'.format)
0       I am a cat
1       I am a dog
2       I am a nan
3    I am a rabbit
dtype: object
```

To avoid applying the function to missing values (and keep them as `NaN`) `na_action='ignore'` can be used:

```
>>> s.map('I am a {}'.format, na_action='ignore')
0     I am a cat
1     I am a dog
2            NaN
3  I am a rabbit
dtype: object
```

pandas.Series.mask

Series.**mask**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *errors='raise'*, *try_cast=False*)

Replace values where the condition is True.

Parameters

cond [bool Series/DataFrame, array-like, or callable] Where *cond* is False, keep the original value. Where True, replace with corresponding value from *other*. If *cond* is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

other [scalar, Series/DataFrame, or callable] Entries where *cond* is True are replaced with corresponding value from *other*. If other is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

inplace [bool, default False] Whether to perform the operation in place on the data.

axis [int, default None] Alignment axis if needed.

level [int, default None] Alignment level if needed.

errors [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won't affect the results and will always coerce to a suitable dtype.

- 'raise' : allow exceptions to be raised.
- 'ignore' : suppress exceptions. On error return original object.

try_cast [bool, default False] Try to cast the result back to the input type (if possible).

Returns

Same type as caller or None if `inplace=True`.

See also:

`DataFrame.where()` Return an object of same shape as self.

Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if `cond` is `False` the element is used; otherwise the corresponding element from the DataFrame `other` is used.

The signature for *`DataFrame.where()`* differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the `mask` documentation in *indexing*.

Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0
dtype: float64
>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0    10
1    10
2    2
3    3
4    4
dtype: int64
>>> s.mask(s > 1, 10)
0     0
1     1
2    10
3    10
4    10
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
4  8  9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0  0 -1
1 -2  3
2 -4 -5
3  6 -7
4 -8  9
>>> df.where(m, -df) == np.where(m, df, -df)
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
```

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```
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

pandas.Series.max

Series.**max**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the maximum of the values over the requested axis.

If you want the *index* of the maximum, use `idxmax`. This isthe equivalent of the `numpy.ndarray` method `argmax`.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded  animal
warm     dog       4
         falcon    2
cold     fish      0
         spider    8
Name: legs, dtype: int64
```

```
>>> s.max()
8
```

Max using level names, as well as indices.

```
>>> s.max(level='blooded')
blooded
warm    4
cold    8
Name: legs, dtype: int64
```

```
>>> s.max(level=0)
blooded
warm    4
cold    8
Name: legs, dtype: int64
```

pandas.Series.mean

Series.**mean**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the mean of the values over the requested axis.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

pandas.Series.median

Series.**median**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the median of the values over the requested axis.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

pandas.Series.memory_usage

Series.**memory_usage**(*index=True*, *deep=False*)

Return the memory usage of the Series.

The memory usage can optionally include the contribution of the index and of elements of *object* dtype.

Parameters

index [bool, default True] Specifies whether to include the memory usage of the Series index.

deep [bool, default False] If True, introspect the data deeply by interrogating *object* dtypes for system-level memory consumption, and include it in the returned value.

Returns

int Bytes of memory consumed.

See also:

numpy.ndarray.nbytes Total bytes consumed by the elements of the array.

DataFrame.memory_usage Bytes consumed by a DataFrame.

Examples

```
>>> s = pd.Series(range(3))
>>> s.memory_usage()
152
```

Not including the index gives the size of the rest of the data, which is necessarily smaller:

```
>>> s.memory_usage(index=False)
24
```

The memory footprint of *object* values is ignored by default:

```
>>> s = pd.Series(["a", "b"])
>>> s.values
array(['a', 'b'], dtype=object)
>>> s.memory_usage()
144
>>> s.memory_usage(deep=True)
244
```

pandas.Series.min

Series.**min**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the minimum of the values over the requested axis.

If you want the *index* of the minimum, use `idxmin`. This isthe equivalent of the `numpy.ndarray` method `argmin`.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded  animal
warm     dog       4
         falcon    2
cold     fish      0
         spider    8
Name: legs, dtype: int64
```

```
>>> s.min()
0
```

Min using level names, as well as indices.

```
>>> s.min(level='blooded')
blooded
warm    2
cold    0
Name: legs, dtype: int64
```

```
>>> s.min(level=0)
blooded
warm    2
cold    0
Name: legs, dtype: int64
```

pandas.Series.mod

Series.**mod**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Modulo of series and other, element-wise (binary operator *mod*).

Equivalent to `series % other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rmod Reverse of the Modulo operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.mod(b, fill_value=0)
a    0.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

pandas.Series.mode

Series.**mode**(*dropna=True*)

Return the mode(s) of the Series.

The mode is the value that appears most often. There can be multiple modes.

Always returns Series even if only one value is returned.

Parameters

dropna [bool, default True] Don't consider counts of NaN/NaT.

New in version 0.24.0.

Returns

Series Modes of the Series in sorted order.

pandas.Series.mul

Series.**mul**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Multiplication of series and other, element-wise (binary operator *mul*).

Equivalent to `series * other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rmul Reverse of the Multiplication operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.multiply(b, fill_value=0)
a    1.0
b    0.0
c    0.0
d    0.0
e    NaN
dtype: float64
```

pandas.Series.multiply

Series.**multiply**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Multiplication of series and other, element-wise (binary operator *mul*).

Equivalent to `series * other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rmul Reverse of the Multiplication operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.multiply(b, fill_value=0)
a    1.0
b    0.0
c    0.0
d    0.0
e    NaN
dtype: float64
```

pandas.Series.ne

Series.**ne**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Not equal to of series and other, element-wise (binary operator *ne*).

Equivalent to `series != other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.ne(b, fill_value=0)
a    False
b     True
c     True
d     True
e     True
dtype: bool
```

pandas.Series.nlargest

`Series.`**`nlargest`**(*n=5*, *keep='first'*)

Return the largest *n* elements.

Parameters

n [int, default 5] Return this many descending sorted values.

keep [{'first', 'last', 'all'}, default 'first'] When there are duplicate values that cannot all fit in a Series of *n* elements:

- **`first`** [return the first *n* occurrences in order] of appearance.
- **`last`** [return the last *n* occurrences in reverse] order of appearance.
- **`all`** [keep all occurrences. This can result in a Series of] size larger than *n*.

Returns

Series The *n* largest values in the Series, sorted in decreasing order.

See also:

`Series.nsmallest` Get the *n* smallest elements.

`Series.sort_values` Sort Series by values.

`Series.head` Return the first *n* rows.

Notes

Faster than `.sort_values(ascending=False).head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,
...                         "Malta": 434000, "Maldives": 434000,
...                         "Brunei": 434000, "Iceland": 337000,
...                         "Nauru": 11300, "Tuvalu": 11300,
...                         "Anguilla": 11300, "Montserrat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy       59000000
France      65000000
Malta         434000
Maldives      434000
Brunei        434000
Iceland       337000
Nauru          11300
Tuvalu         11300
Anguilla       11300
Montserrat      5200
dtype: int64
```

The *n* largest elements where `n=5` by default.

```
>>> s.nlargest()
France      65000000
Italy       59000000
Malta         434000
Maldives      434000
Brunei        434000
dtype: int64
```

The *n* largest elements where `n=3`. Default *keep* value is 'first' so Malta will be kept.

```
>>> s.nlargest(3)
France    65000000
Italy     59000000
Malta       434000
dtype: int64
```

The *n* largest elements where `n=3` and keeping the last duplicates. Brunei will be kept since it is the last with value 434000 based on the index order.

```
>>> s.nlargest(3, keep='last')
France      65000000
Italy       59000000
Brunei        434000
dtype: int64
```

The *n* largest elements where `n=3` with all duplicates kept. Note that the returned Series has five elements due to the three duplicates.

```
>>> s.nlargest(3, keep='all')
France      65000000
Italy       59000000
Malta         434000
Maldives      434000
Brunei        434000
dtype: int64
```

pandas.Series.notna

Series.**notna**()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or `numpy.NaN`, get mapped to False values.

Returns

Series Mask of bool values for each element in Series that indicates whether an element is not an NA value.

See also:

Series.notnull Alias of notna.

Series.isna Boolean inverse of notna.

Series.dropna Omit axes labels with missing values.

notna Top-level notna.

Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.notna()
     age   born  name    toy
0   True  False  True  False
1   True   True  True   True
2  False   True  True   True
```

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0     True
1     True
2    False
dtype: bool
```

pandas.Series.notnull

Series.**notnull**()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or `numpy.NaN`, get mapped to False values.

Returns

Series Mask of bool values for each element in Series that indicates whether an element is not an NA value.

See also:

Series.notnull Alias of notna.

Series.isna Boolean inverse of notna.

Series.dropna Omit axes labels with missing values.

notna Top-level notna.

Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.notna()
     age   born  name    toy
```

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```
0   True  False  True  False
1   True   True  True   True
2  False   True  True   True
```

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0     True
1     True
2    False
dtype: bool
```

pandas.Series.nsmallest

Series.**nsmallest**(*n=5*, *keep='first'*)

Return the smallest *n* elements.

Parameters

n [int, default 5] Return this many ascending sorted values.

keep [{'first', 'last', 'all'}, default 'first'] When there are duplicate values that cannot all fit in a Series of *n* elements:

- **first** [return the first *n* occurrences in order] of appearance.
- **last** [return the last *n* occurrences in reverse] order of appearance.
- **all** [keep all occurrences. This can result in a Series of] size larger than *n*.

Returns

Series The *n* smallest values in the Series, sorted in increasing order.

See also:

Series.nlargest Get the *n* largest elements.

Series.sort_values Sort Series by values.

Series.head Return the first *n* rows.

Notes

Faster than `.sort_values().head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,
...                         "Brunei": 434000, "Malta": 434000,
...                         "Maldives": 434000, "Iceland": 337000,
...                         "Nauru": 11300, "Tuvalu": 11300,
...                         "Anguilla": 11300, "Montserrat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy       59000000
France      65000000
Brunei        434000
Malta         434000
Maldives      434000
Iceland       337000
Nauru          11300
Tuvalu         11300
Anguilla       11300
Montserrat      5200
dtype: int64
```

The *n* smallest elements where `n=5` by default.

```
>>> s.nsmallest()
Montserrat    5200
Nauru        11300
Tuvalu       11300
Anguilla     11300
Iceland     337000
dtype: int64
```

The *n* smallest elements where `n=3`. Default *keep* value is 'first' so Nauru and Tuvalu will be kept.

```
>>> s.nsmallest(3)
Montserrat   5200
Nauru       11300
Tuvalu      11300
dtype: int64
```

The *n* smallest elements where `n=3` and keeping the last duplicates. Anguilla and Tuvalu will be kept since they are the last with value 11300 based on the index order.

```
>>> s.nsmallest(3, keep='last')
Montserrat   5200
Anguilla    11300
Tuvalu      11300
dtype: int64
```

The *n* smallest elements where `n=3` with all duplicates kept. Note that the returned Series has four elements due to the three duplicates.

```
>>> s.nsmallest(3, keep='all')
Montserrat   5200
Nauru        11300
Tuvalu       11300
Anguilla     11300
dtype: int64
```

pandas.Series.nunique

Series.**nunique**(*dropna=True*)

Return number of unique elements in the object.

Excludes NA values by default.

Parameters

dropna [bool, default True] Don't include NaN in the count.

Returns

int

See also:

DataFrame.nunique Method nunique for DataFrame.

Series.count Count non-NA/null observations in the Series.

Examples

```
>>> s = pd.Series([1, 3, 5, 7, 7])
>>> s
0    1
1    3
2    5
3    7
4    7
dtype: int64
```

```
>>> s.nunique()
4
```

pandas.Series.pad

Series.**pad**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *DataFrame.fillna()* with `method='ffill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.Series.pct_change

Series.**pct_change**(*periods=1*, *fill_method='pad'*, *limit=None*, *freq=None*, ***kwargs*)

Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

Parameters

periods [int, default 1] Periods to shift for forming percent change.

fill_method [str, default 'pad'] How to handle NAs before computing percent changes.

limit [int, default None] The number of consecutive NAs to fill before stopping.

freq [DateOffset, timedelta, or str, optional] Increment to use from time series API (e.g. 'M' or BDay()).

****kwargs** Additional keyword arguments are passed into *DataFrame.shift* or *Series.shift*.

Returns

chg [Series or DataFrame] The same type as the calling object.

See also:

Series.diff Compute the difference of two elements in a Series.

DataFrame.diff Compute the difference of two elements in a DataFrame.

Series.shift Shift the index by some number of periods.

DataFrame.shift Shift the index by some number of periods.

Examples

Series

```
>>> s = pd.Series([90, 91, 85])
>>> s
0    90
1    91
2    85
dtype: int64
```

```
>>> s.pct_change()
0         NaN
1    0.011111
2   -0.065934
dtype: float64
```

```
>>> s.pct_change(periods=2)
0         NaN
1         NaN
2   -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

```
>>> s = pd.Series([90, 91, None, 85])
>>> s
0    90.0
1    91.0
2     NaN
3    85.0
dtype: float64
```

```
>>> s.pct_change(fill_method='ffill')
0         NaN
1    0.011111
2    0.000000
3   -0.065934
dtype: float64
```

DataFrame

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

```
>>> df = pd.DataFrame({
...     'FR': [4.0405, 4.0963, 4.3149],
...     'GR': [1.7246, 1.7482, 1.8519],
...     'IT': [804.74, 810.01, 860.13]},
...     index=['1980-01-01', '1980-02-01', '1980-03-01'])
>>> df
                FR      GR      IT
1980-01-01  4.0405  1.7246  804.74
1980-02-01  4.0963  1.7482  810.01
1980-03-01  4.3149  1.8519  860.13
```

```
>>> df.pct_change()
                  FR        GR        IT
1980-01-01       NaN       NaN       NaN
1980-02-01  0.013810  0.013684  0.006549
1980-03-01  0.053365  0.059318  0.061876
```

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

```
>>> df = pd.DataFrame({
...     '2016': [1769950, 30586265],
...     '2015': [1500923, 40912316],
...     '2014': [1371819, 41403351]},
...     index=['GOOG', 'APPL'])
>>> df
          2016      2015      2014
GOOG   1769950   1500923   1371819
APPL  30586265  40912316  41403351
```

```
>>> df.pct_change(axis='columns')
      2016      2015      2014
GOOG   NaN -0.151997 -0.086016
APPL   NaN  0.337604  0.012002
```

pandas.Series.pipe

Series.**pipe**(*func*, **args*, ***kwargs*)

Apply func(self, *args, **kwargs).

Parameters

func [function] Function to apply to the Series/DataFrame. `args`, and `kwargs` are passed into `func`. Alternatively a `(callable, data_keyword)` tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the Series/DataFrame.

args [iterable, optional] Positional arguments passed into `func`.

kwargs [mapping, optional] A dictionary of keyword arguments passed into `func`.

Returns

object [the return type of `func`.]

See also:

DataFrame.apply Apply a function along input axis of DataFrame.

DataFrame.applymap Apply a function elementwise on a whole DataFrame.

Series.map Apply a mapping correspondence on a *Series*.

Notes

Use `.pipe` when chaining together functions that expect Series, DataFrames or GroupBy objects. Instead of writing

```
>>> func(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe(func, arg2=b, arg3=c)
... )
```

If you have a function that takes the data as (say) the second argument, pass a tuple indicating which keyword expects the data. For example, suppose `f` takes its data as `arg2`:

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe((func, 'arg2'), arg1=a, arg3=c)
...  )
```

pandas.Series.plot

Series.**plot**(**args*, ***kwargs*)

Make plots of Series or DataFrame.

Uses the backend specified by the option `plotting.backend`. By default, matplotlib is used.

Parameters

data [Series or DataFrame] The object for which the method is called.

x [label or position, default None] Only used if data is a DataFrame.

y [label, position or list of label, positions, default None] Allows plotting of one column versus another. Only used if data is a DataFrame.

kind [str] The kind of plot to produce:

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot.

ax [matplotlib axes object, default None] An axes of the current figure.

subplots [bool, default False] Make separate subplots for each column.

sharex [bool, default True if ax is None else False] In case `subplots=True`, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and `sharex=True` will alter all x axis labels for all axis in a figure.

sharey [bool, default False] In case `subplots=True`, share y axis and set some y axis labels to invisible.

layout [tuple, optional] (rows, columns) for the layout of subplots.

figsize [a tuple (width, height) in inches] Size of a figure object.

use_index [bool, default True] Use index as ticks for x axis.

title [str or list] Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and *subplots* is True, print each item in the list above the corresponding subplot.

grid [bool, default None (matlab style default)] Axis grid lines.

legend [bool or {'reverse'}] Place legend on axis subplots.

style [list or dict] The matplotlib line style per column.

logx [bool or 'sym', default False] Use log scaling or symlog scaling on x axis. .. versionchanged:: 0.25.0

logy [bool or 'sym' default False] Use log scaling or symlog scaling on y axis. .. versionchanged:: 0.25.0

loglog [bool or 'sym', default False] Use log scaling or symlog scaling on both x and y axes. .. versionchanged:: 0.25.0

xticks [sequence] Values to use for the xticks.

yticks [sequence] Values to use for the yticks.

xlim [2-tuple/list] Set the x limits of the current axes.

ylim [2-tuple/list] Set the y limits of the current axes.

xlabel [label, optional] Name to use for the xlabel on x-axis. Default uses index name as xlabel, or the x-column name for planar plots.

New in version 1.1.0.

Changed in version 1.2.0: Now applicable to planar plots (*scatter*, *hexbin*).

ylabel [label, optional] Name to use for the ylabel on y-axis. Default will show no ylabel, or the y-column name for planar plots.

New in version 1.1.0.

Changed in version 1.2.0: Now applicable to planar plots (*scatter*, *hexbin*).

rot [int, default None] Rotation for ticks (xticks for vertical, yticks for horizontal plots).

fontsize [int, default None] Font size for xticks and yticks.

colormap [str or matplotlib colormap object, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar [bool, optional] If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots).

position [float] Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center).

table [bool, Series or DataFrame, default False] If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr [DataFrame, Series, array-like, dict and str] See *Plotting with Error Bars* for detail.

xerr [DataFrame, Series, array-like, dict and str] Equivalent to yerr.

stacked [bool, default False in line and bar plots, and True in area plot] If True, create stacked plot.

sort_columns [bool, default False] Sort column names to determine plot ordering.

secondary_y [bool or sequence, default False] Whether to plot on the secondary y-axis if a list/tuple, which columns to plot on secondary y-axis.

mark_right [bool, default True] When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend.

include_bool [bool, default is False] If True, boolean values can be plotted.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

****kwargs** Options to pass to matplotlib plotting method.

Returns

`matplotlib.axes.Axes` or numpy.ndarray of them If the backend is not the default matplotlib one, the return value will be the object returned by the backend.

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

pandas.Series.pop

`Series.`**`pop`**`(`*`item`*`)`

Return item and drops from series. Raise KeyError if not found.

Parameters

item [label] Index of the element that needs to be removed.

Returns

Value that is popped from series.

Examples

```
>>> ser = pd.Series([1,2,3])
```

```
>>> ser.pop(0)
1
```

```
>>> ser
1    2
2    3
dtype: int64
```

pandas.Series.pow

Series.**pow**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Exponential power of series and other, element-wise (binary operator *pow*).

Equivalent to `series ** other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rpow Reverse of the Exponential power operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.pow(b, fill_value=0)
a    1.0
b    1.0
c    1.0
d    0.0
e    NaN
dtype: float64
```

pandas.Series.prod

Series.**prod**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, *min_count=0*, ***kwargs*)

Return the product of the values over the requested axis.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

By default, the product of an empty or all-NA Series is `1`

```
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

pandas.Series.product

Series.**product**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, *min_count=0*, ***kwargs*)

Return the product of the values over the requested axis.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

By default, the product of an empty or all-NA Series is `1`

```
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

pandas.Series.quantile

`Series.`**`quantile`**(*q=0.5*, *interpolation='linear'*)

Return value at the given quantile.

Parameters

q [float or array-like, default 0.5 (50% quantile)] The quantile(s) to compute, which can lie in range: 0 <= q <= 1.

interpolation [{'linear', 'lower', 'higher', 'midpoint', 'nearest'}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points *i* and *j*:

- linear: *i* + (*j* - *i*) * *fraction*, where *fraction* is the fractional part of the index surrounded by *i* and *j*.
- lower: *i*.
- higher: *j*.
- nearest: *i* or *j* whichever is nearest.
- midpoint: (*i* + *j*) / 2.

Returns

float or Series If `q` is an array, a Series will be returned where the index is `q` and the values are the quantiles, otherwise a float will be returned.

See also:

`core.window.Rolling.quantile` Calculate the rolling quantile.

`numpy.percentile` Returns the q-th percentile(s) of the array elements.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.quantile(.5)
2.5
>>> s.quantile([.25, .5, .75])
0.25    1.75
0.50    2.50
0.75    3.25
dtype: float64
```

pandas.Series.radd

Series.**radd**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Addition of series and other, element-wise (binary operator *radd*).

Equivalent to `other + series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.add Element-wise Addition, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.add(b, fill_value=0)
```

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```
a    2.0
b    1.0
c    1.0
d    1.0
e    NaN
dtype: float64
```

pandas.Series.rank

Series.**rank**(*axis=0*, *method='average'*, *numeric_only=None*, *na_option='keep'*, *ascending=True*, *pct=False*)

Compute numerical data ranks (1 through n) along axis.

By default, equal values are assigned a rank that is the average of the ranks of those values.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] Index to direct ranking.

method [{'average', 'min', 'max', 'first', 'dense'}, default 'average'] How to rank the group of records that have the same value (i.e. ties):

- average: average rank of the group
- min: lowest rank in the group
- max: highest rank in the group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups.

numeric_only [bool, optional] For DataFrame objects, rank only numeric columns if set to True.

na_option [{'keep', 'top', 'bottom'}, default 'keep'] How to rank NaN values:

- keep: assign NaN rank to NaN values
- top: assign smallest rank to NaN values if ascending
- bottom: assign highest rank to NaN values if ascending.

ascending [bool, default True] Whether or not the elements should be ranked in ascending order.

pct [bool, default False] Whether or not to display the returned rankings in percentile form.

Returns

same type as caller Return a Series or DataFrame with data ranks as values.

See also:

core.groupby.GroupBy.rank Rank of values within each group.

Examples

```
>>> df = pd.DataFrame(data={'Animal': ['cat', 'penguin', 'dog',
...                                    'spider', 'snake'],
...                         'Number_legs': [4, 2, 4, 8, np.nan]})
>>> df
    Animal  Number_legs
0      cat          4.0
1  penguin          2.0
2      dog          4.0
3   spider          8.0
4    snake          NaN
```

The following example shows how the method behaves with the above parameters:

- default_rank: this is the default behaviour obtained without using any parameter.
- max_rank: setting `method = 'max'` the records that have the same values are ranked using the highest rank (e.g.: since 'cat' and 'dog' are both in the 2nd and 3rd position, rank 3 is assigned.)
- NA_bottom: choosing `na_option = 'bottom'`, if there are records with NaN values they are placed at the bottom of the ranking.
- pct_rank: when setting `pct = True`, the ranking is expressed as percentile rank.

```
>>> df['default_rank'] = df['Number_legs'].rank()
>>> df['max_rank'] = df['Number_legs'].rank(method='max')
>>> df['NA_bottom'] = df['Number_legs'].rank(na_option='bottom')
>>> df['pct_rank'] = df['Number_legs'].rank(pct=True)
>>> df
    Animal  Number_legs  default_rank  max_rank  NA_bottom  pct_rank
0      cat          4.0           2.5       3.0        2.5     0.625
1  penguin          2.0           1.0       1.0        1.0     0.250
2      dog          4.0           2.5       3.0        2.5     0.625
3   spider          8.0           4.0       4.0        4.0     1.000
4    snake          NaN           NaN       NaN        5.0       NaN
```

pandas.Series.ravel

`Series.`**`ravel`**(*order='C'*)

Return the flattened underlying data as an ndarray.

Returns

numpy.ndarray or ndarray-like Flattened data of the Series.

See also:

`numpy.ndarray.ravel` Return a flattened array.

pandas.Series.rdiv

Series.**rdiv**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Floating division of series and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.truediv Element-wise Floating division, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
d    0.0
e    NaN
dtype: float64
```

pandas.Series.rdivmod

Series.**rdivmod**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Integer division and modulo of series and other, element-wise (binary operator *rdivmod*).

Equivalent to `other divmod series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

2-Tuple of Series The result of the operation.

See also:

Series.divmod Element-wise Integer division and modulo, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divmod(b, fill_value=0)
(a    1.0
 b    NaN
 c    NaN
 d    0.0
 e    NaN
 dtype: float64,
 a    0.0
 b    NaN
 c    NaN
 d    0.0
 e    NaN
 dtype: float64)
```

pandas.Series.reindex

Series.**reindex**(*index=None*, ***kwargs*)

Conform Series to new index with optional filling logic.

Places NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`.

Parameters

index [array-like, optional] New labels / index to conform to, should be specified using keywords. Preferably an Index object to avoid duplicating data.

method [{None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don't fill gaps
- pad / ffill: Propagate last valid observation forward to next valid.
- backfill / bfill: Use next valid observation to fill gap.
- nearest: Use nearest valid observations to fill gap.

copy [bool, default True] Return a new object, even if the passed indexes are the same.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any "compatible" value.

limit [int, default None] Maximum number of consecutive elements to forward or backward fill.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

Returns

Series with changed index.

See also:

DataFrame.set_index Set row labels.

DataFrame.reset_index Remove row labels or move them to new columns.

DataFrame.reindex_like Change to same indices as other DataFrame.

Examples

`DataFrame.reindex` supports two calling conventions

- `(index=index_labels, columns=column_labels, ...)`
- `(labels, axis={'index', 'columns'}, ...)`

We *highly* recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({'http_status': [200, 200, 404, 404, 301],
...                    'response_time': [0.04, 0.02, 0.07, 0.08, 1.0]},
...                    index=index)
>>> df
           http_status  response_time
Firefox            200           0.04
Chrome             200           0.02
Safari             404           0.07
IE10               404           0.08
Konqueror          301           1.00
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned `NaN`.

```
>>> new_index = ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10',
...              'Chrome']
>>> df.reindex(new_index)
               http_status  response_time
Safari               404.0           0.07
Iceweasel              NaN            NaN
Comodo Dragon          NaN            NaN
IE10                 404.0           0.08
Chrome               200.0           0.02
```

We can fill in the missing values by passing a value to the keyword `fill_value`. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword `method` to fill the `NaN` values.

```
>>> df.reindex(new_index, fill_value=0)
               http_status  response_time
Safari                 404           0.07
Iceweasel                0           0.00
Comodo Dragon            0           0.00
IE10                   404           0.08
Chrome                 200           0.02
```

```
>>> df.reindex(new_index, fill_value='missing')
              http_status response_time
Safari                404          0.07
Iceweasel         missing       missing
Comodo Dragon     missing       missing
IE10                  404          0.08
Chrome                200          0.02
```

We can also reindex the columns.

```
>>> df.reindex(columns=['http_status', 'user_agent'])
           http_status  user_agent
Firefox            200         NaN
Chrome             200         NaN
Safari             404         NaN
IE10               404         NaN
Konqueror          301         NaN
```

Or we can use "axis-style" keyword arguments

```
>>> df.reindex(['http_status', 'user_agent'], axis="columns")
           http_status  user_agent
Firefox            200         NaN
Chrome             200         NaN
Safari             404         NaN
IE10               404         NaN
Konqueror          301         NaN
```

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame({"prices": [100, 101, np.nan, 100, 89, 88]},
...                    index=date_index)
>>> df2
            prices
2010-01-01   100.0
2010-01-02   101.0
2010-01-03     NaN
2010-01-04   100.0
2010-01-05    89.0
2010-01-06    88.0
```

Suppose we decide to expand the dataframe to cover a wider date range.

```
>>> date_index2 = pd.date_range('12/29/2009', periods=10, freq='D')
>>> df2.reindex(date_index2)
            prices
2009-12-29     NaN
2009-12-30     NaN
2009-12-31     NaN
2010-01-01   100.0
2010-01-02   101.0
2010-01-03     NaN
2010-01-04   100.0
2010-01-05    89.0
2010-01-06    88.0
2010-01-07     NaN
```

The index entries that did not have a value in the original data frame (for example, '2009-12-29') are by default filled with `NaN`. If desired, we can fill in the missing values using one of several options.

For example, to back-propagate the last valid value to fill the `NaN` values, pass `bfill` as an argument to the `method` keyword.

```
>>> df2.reindex(date_index2, method='bfill')
            prices
```

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```
2009-12-29   100.0
2009-12-30   100.0
2009-12-31   100.0
2010-01-01   100.0
2010-01-02   101.0
2010-01-03     NaN
2010-01-04   100.0
2010-01-05    89.0
2010-01-06    88.0
2010-01-07     NaN
```

Please note that the `NaN` value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the `NaN` values present in the original dataframe, use the `fillna()` method.

See the *user guide* for more.

pandas.Series.reindex_like

`Series.`**`reindex_like`**(*other*, *method=None*, *copy=True*, *limit=None*, *tolerance=None*)

Return an object with matching indices as other object.

Conform the object to the same index on all axes. Optional filling logic, placing NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False.

Parameters

other [Object of the same data type] Its row and column indices are used to define the new indices of this object.

method [{None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap.

copy [bool, default True] Return a new object, even if the passed indexes are the same.

limit [int, default None] Maximum number of consecutive labels to fill for inexact matches.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

Returns

Series or DataFrame Same type as caller, but with changed indices on each axis.

See also:

DataFrame.set_index Set row labels.

DataFrame.reset_index Remove row labels or move them to new columns.

DataFrame.reindex Change to new indices or expand indices.

Notes

Same as calling `.reindex(index=other.index, columns=other.columns,...)`.

Examples

```
>>> df1 = pd.DataFrame([[24.3, 75.7, 'high'],
...                     [31, 87.8, 'high'],
...                     [22, 71.6, 'medium'],
...                     [35, 95, 'medium']],
...                    columns=['temp_celsius', 'temp_fahrenheit',
...                             'windspeed'],
...                    index=pd.date_range(start='2014-02-12',
...                                        end='2014-02-15', freq='D'))
```

```
>>> df1
            temp_celsius  temp_fahrenheit windspeed
2014-02-12          24.3             75.7      high
2014-02-13          31.0             87.8      high
2014-02-14          22.0             71.6    medium
2014-02-15          35.0             95.0    medium
```

```
>>> df2 = pd.DataFrame([[28, 'low'],
...                     [30, 'low'],
...                     [35.1, 'medium']],
...                    columns=['temp_celsius', 'windspeed'],
...                    index=pd.DatetimeIndex(['2014-02-12', '2014-02-13',
...                                            '2014-02-15']))
```

```
>>> df2
            temp_celsius windspeed
2014-02-12          28.0       low
2014-02-13          30.0       low
2014-02-15          35.1    medium
```

```
>>> df2.reindex_like(df1)
            temp_celsius  temp_fahrenheit windspeed
2014-02-12          28.0              NaN       low
2014-02-13          30.0              NaN       low
2014-02-14           NaN              NaN       NaN
2014-02-15          35.1              NaN    medium
```

pandas.Series.rename

Series.**rename**(*index=None*, ***, *axis=None*, *copy=True*, *inplace=False*, *level=None*, *errors='ignore'*)

Alter Series index labels or name.

Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is. Extra labels listed don't throw an error.

Alternatively, change `Series.name` with a scalar value.

See the *user guide* for more.

Parameters

axis [{0 or "index"}] Unused. Accepted for compatibility with DataFrame method only.

index [scalar, hashable sequence, dict-like or function, optional] Functions or dict-like are transformations to apply to the index. Scalar or hashable sequence-like will alter the `Series.name` attribute.

****kwargs** Additional keyword arguments passed to the function. Only the "inplace" keyword is used.

Returns

Series or None Series with index labels or name altered or None if `inplace=True`.

See also:

DataFrame.rename Corresponding DataFrame method.

Series.rename_axis Set the name of the axis.

Examples

```
>>> s = pd.Series([1, 2, 3])
>>> s
0    1
1    2
2    3
dtype: int64
>>> s.rename("my_name")  # scalar, changes Series.name
0    1
1    2
2    3
Name: my_name, dtype: int64
>>> s.rename(lambda x: x ** 2)  # function, changes labels
0    1
1    2
4    3
dtype: int64
>>> s.rename({1: 3, 2: 5})  # mapping, changes labels
0    1
3    2
5    3
dtype: int64
```

pandas.Series.rename_axis

Series.**rename_axis**(*mapper=None*, *index=None*, *columns=None*, *axis=None*, *copy=True*, *inplace=False*)

Set the name of the axis for the index or columns.

Parameters

mapper [scalar, list-like, optional] Value to set the axis name attribute.

index, columns [scalar, list-like, dict-like or function, optional] A scalar, list-like, dict-like or functions transformations to apply to that axis' values. Note that the `columns` parameter is not allowed if the object is a Series. This parameter only apply for DataFrame type objects.

Use either `mapper` and `axis` to specify the axis to target with `mapper`, or `index` and/or `columns`.

Changed in version 0.24.0.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to rename.

copy [bool, default True] Also copy underlying data.

inplace [bool, default False] Modifies the object directly, instead of creating a new Series or DataFrame.

Returns

Series, DataFrame, or None The same type as the caller or None if `inplace=True`.

See also:

Series.rename Alter Series index labels or name.

DataFrame.rename Alter DataFrame index labels or name.

Index.rename Set new names on index.

Notes

`DataFrame.rename_axis` supports two calling conventions

- `(index=index_mapper, columns=columns_mapper, ...)`
- `(mapper, axis={'index', 'columns'}, ...)`

The first calling convention will only modify the names of the index and/or the names of the Index object that is the columns. In this case, the parameter `copy` is ignored.

The second calling convention will modify the names of the corresponding index if mapper is a list or a scalar. However, if mapper is dict-like or a function, it will use the deprecated behavior of modifying the axis *labels*.

We *highly* recommend using keyword arguments to clarify your intent.

Examples

Series

```
>>> s = pd.Series(["dog", "cat", "monkey"])
>>> s
0       dog
1       cat
2    monkey
dtype: object
>>> s.rename_axis("animal")
animal
0    dog
1    cat
2    monkey
dtype: object
```

DataFrame

```
>>> df = pd.DataFrame({"num_legs": [4, 4, 2],
...                    "num_arms": [0, 0, 2]},
...                   ["dog", "cat", "monkey"])
>>> df
        num_legs  num_arms
dog             4         0
cat             4         0
monkey          2         2
>>> df = df.rename_axis("animal")
>>> df
        num_legs  num_arms
animal
dog             4         0
cat             4         0
monkey          2         2
>>> df = df.rename_axis("limbs", axis="columns")
>>> df
limbs   num_legs  num_arms
animal
dog             4         0
cat             4         0
monkey          2         2
```

MultiIndex

```
>>> df.index = pd.MultiIndex.from_product([['mammal'],
...                                        ['dog', 'cat', 'monkey']],
...                                       names=['type', 'name'])
>>> df
limbs          num_legs  num_arms
type   name
mammal dog             4         0
       cat             4         0
       monkey          2         2
```

```
>>> df.rename_axis(index={'type': 'class'})
limbs          num_legs  num_arms
class  name
```

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```
mammal dog             4          0
       cat             4          0
       monkey          2          2
```

```
>>> df.rename_axis(columns=str.upper)
LIMBS          num_legs  num_arms
type   name
mammal dog             4          0
       cat             4          0
       monkey          2          2
```

pandas.Series.reorder_levels

Series.**reorder_levels**(*order*)

Rearrange index levels using input order.

May not drop or duplicate levels.

Parameters

order [list of int representing new level order] Reference level by number or key.

Returns

type of caller (new object)

pandas.Series.repeat

Series.**repeat**(*repeats*, *axis=None*)

Repeat elements of a Series.

Returns a new Series where each element of the current Series is repeated consecutively a given number of times.

Parameters

repeats [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty Series.

axis [None] Must be `None`. Has no effect but is accepted for compatibility with numpy.

Returns

Series Newly created Series with repeated elements.

See also:

Index.repeat Equivalent function for Index.

numpy.repeat Similar method for `numpy.ndarray`.

Examples

```
>>> s = pd.Series(['a', 'b', 'c'])
>>> s
0    a
1    b
2    c
dtype: object
>>> s.repeat(2)
0    a
0    a
1    b
1    b
2    c
2    c
dtype: object
>>> s.repeat([1, 2, 3])
0    a
1    b
1    b
2    c
2    c
2    c
dtype: object
```

pandas.Series.replace

Series.**replace**(*to_replace=None*, *value=None*, *inplace=False*, *limit=None*, *regex=False*, *method='pad'*)

Replace values given in *to_replace* with *value*.

Values of the Series are replaced with other values dynamically. This differs from updating with `.loc` or `.iloc`, which require you to specify a location to update with some value.

Parameters

to_replace [str, regex, list, dict, Series, int, float, or None] How to find the values that will be replaced.

- numeric, str or regex:
  - numeric: numeric values equal to *to_replace* will be replaced with *value*
  - str: string exactly matching *to_replace* will be replaced with *value*
  - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str, regex and numeric rules apply as above.
- dict:
  - Dicts can be used to specify different replacement values for different existing values. For example, `{'a': 'b', 'y': 'z'}` replaces the value 'a' with

'b' and 'y' with 'z'. To use a dict in this way the *value* parameter should be *None*.

- For a DataFrame a dict can specify that different values should be replaced in different columns. For example, `{'a': 1, 'b': 'z'}` looks for the value 1 in column 'a' and the value 'z' in column 'b' and replaces these values with whatever is specified in *value*. The *value* parameter should not be `None` in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- For a DataFrame nested dictionaries, e.g., `{'a': {'b': np.nan}}`, are read as follows: look in column 'a' for the value 'b' and replace it with NaN. The *value* parameter should be `None` to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.

- None:
  - This means that the *regex* argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value [scalar, dict, list, str, regex, default None] Value to replace any values matching *to_replace* with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace [bool, default False] If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit [int or None, default None] Maximum size gap to forward or backward fill.

regex [bool or same types as *to_replace*, default False] Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case *to_replace* must be `None`.

method [{'pad', 'ffill', 'bfill', *None*}] The method to use when for replacement, when *to_replace* is a scalar, list or tuple and *value* is `None`.

Returns

Series or None Object after replacement or None if `inplace=True`.

Raises

AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is not a scalar, array-like, `dict`, or `None`
- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.
- When replacing multiple `bool` or `datetime64` objects and the arguments to *to_replace* does not match the type of the value being replaced

ValueError

- If a `list` or an `ndarray` is passed to *to_replace* and *value* but they are not the same length.

See also:

Series.fillna Fill NA values.

Series.where Replace values based on boolean condition.

Series.str.replace Simple string replacement.

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.
- When dict is used as the *to_replace* value, it is like key(s) in the dict are the to_replace part and value(s) in the dict are the value parameter.

Examples

Scalar `to_replace` and `value`

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0    5
1    1
2    2
3    3
4    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
...                    'B': [5, 6, 7, 8, 9],
...                    'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A  B  C
0  5  5  a
1  1  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

List-like `to_replace`

```
>>> df.replace([0, 1, 2, 3], 4)
   A  B  C
0  4  5  a
1  4  6  b
2  4  7  c
3  4  8  d
4  4  9  e
```

```
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A  B  C
0  4  5  a
1  3  6  b
2  2  7  c
3  1  8  d
4  4  9  e
```

```
>>> s.replace([1, 2], method='bfill')
0    0
1    3
2    3
3    3
4    4
dtype: int64
```

dict-like `to_replace`

```
>>> df.replace({0: 10, 1: 100})
     A  B  C
0   10  5  a
1  100  6  b
2    2  7  c
3    3  8  d
4    4  9  e
```

```
>>> df.replace({'A': 0, 'B': 5}, 100)
     A    B  C
0  100  100  a
1    1    6  b
2    2    7  c
3    3    8  d
4    4    9  e
```

```
>>> df.replace({'A': {0: 100, 4: 400}})
     A  B  C
0  100  5  a
1    1  6  b
2    2  7  c
3    3  8  d
4  400  9  e
```

Regular expression `to_replace`

```
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
...                    'B': ['abc', 'bar', 'xyz']})
>>> df.replace(to_replace=r'^ba.$', value='new', regex=True)
      A    B
```

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```
0   new  abc
1   foo  new
2  bait  xyz
```

```
>>> df.replace({'A': r'^ba.$'}, {'A': 'new'}, regex=True)
      A    B
0   new  abc
1   foo  bar
2  bait  xyz
```

```
>>> df.replace(regex=r'^ba.$', value='new')
      A    B
0   new  abc
1   foo  new
2  bait  xyz
```

```
>>> df.replace(regex={r'^ba.$': 'new', 'foo': 'xyz'})
      A    B
0   new  abc
1   xyz  new
2  bait  xyz
```

```
>>> df.replace(regex=[r'^ba.$', 'foo'], value='new')
      A    B
0   new  abc
1   new  new
2  bait  xyz
```

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the *to_replace* parameter:

```
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
```

When one uses a dict as the *to_replace* value, it is like the value(s) in the dict are equal to the *value* parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None)`:

```
>>> s.replace({'a': None})
0      10
1    None
2    None
3       b
4    None
dtype: object
```

When `value=None` and *to_replace* is a scalar, list or tuple, *replace* uses the method parameter (default 'pad') to do the replacement. So this is why the 'a' values are being replaced by 10 in rows 1 and 2 and 'b' in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad')`:

```
>>> s.replace('a', None)
0    10
1    10
2    10
```

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```
3     b
4     b
dtype: object
```

pandas.Series.resample

Series.**resample**(*rule*, *axis=0*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *base=None*, *on=None*, *level=None*, *origin='start_day'*, *offset=None*)

Resample time-series data.

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (*DatetimeIndex*, *PeriodIndex*, or *TimedeltaIndex*), or pass datetime-like values to the *on* or *level* keyword.

Parameters

rule [DateOffset, Timedelta or str] The offset string or object representing target conversion.

axis [{0 or 'index', 1 or 'columns'}, default 0] Which axis to use for up- or down-sampling. For *Series* this will default to 0, i.e. along the rows. Must be *DatetimeIndex*, *TimedeltaIndex* or *PeriodIndex*.

closed [{'right', 'left'}, default None] Which side of bin interval is closed. The default is 'left' for all frequency offsets except for 'M', 'A', 'Q', 'BM', 'BA', 'BQ', and 'W' which all have a default of 'right'.

label [{'right', 'left'}, default None] Which bin edge label to label bucket with. The default is 'left' for all frequency offsets except for 'M', 'A', 'Q', 'BM', 'BA', 'BQ', and 'W' which all have a default of 'right'.

convention [{'start', 'end', 's', 'e'}, default 'start'] For *PeriodIndex* only, controls whether to use the start or end of *rule*.

kind [{'timestamp', 'period'}, optional, default None] Pass 'timestamp' to convert the resulting index to a *DateTimeIndex* or 'period' to convert it to a *PeriodIndex*. By default the input representation is retained.

loffset [timedelta, default None] Adjust the resampled time labels.

Deprecated since version 1.1.0: You should add the loffset to the *df.index* after the resample. See below.

base [int, default 0] For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0.

Deprecated since version 1.1.0: The new arguments that you should use are 'offset' or 'origin'.

on [str, optional] For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.

level [str or int, optional] For a MultiIndex, level (name or number) to use for resampling. *level* must be datetime-like.

origin [{'epoch', 'start', 'start_day'}, Timestamp or str, default 'start_day'] The timestamp on which to adjust the grouping. The timezone of origin must match the timezone of the index. If a timestamp is not used, these values are also supported:

- 'epoch': *origin* is 1970-01-01
- 'start': *origin* is the first value of the timeseries
- 'start_day': *origin* is the first day at midnight of the timeseries

New in version 1.1.0.

offset [Timedelta or str, default is None] An offset timedelta added to the origin.

New in version 1.1.0.

Returns

Resampler object

See also:

groupby Group by mapping, function, label, or list of labels.

Series.resample Resample a Series.

DataFrame.resample Resample a DataFrame.

Notes

See the user guide for more.

To learn more about the offset strings, please see this link.

Examples

Start by creating a series with 9 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series
2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```
>>> series.resample('3T').sum()
2000-01-01 00:00:00     3
2000-01-01 00:03:00    12
2000-01-01 00:06:00    21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket `2000-01-01 00:03:00` contains the value 3, but the summed value in the resampled bucket with the label `2000-01-01 00:03:00` does not include 3 (if

it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00     3
2000-01-01 00:06:00    12
2000-01-01 00:09:00    21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00     0
2000-01-01 00:03:00     6
2000-01-01 00:06:00    15
2000-01-01 00:09:00    15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.

```
>>> series.resample('30S').asfreq()[0:5]   # Select first 5 rows
2000-01-01 00:00:00   0.0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00   1.0
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00   2.0
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the `NaN` values using the `pad` method.

```
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    0
2000-01-01 00:01:00    1
2000-01-01 00:01:30    1
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the `NaN` values using the `bfill` method.

```
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    1
2000-01-01 00:01:00    1
2000-01-01 00:01:30    2
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Pass a custom function via `apply`

```
>>> def custom_resampler(array_like):
...     return np.sum(array_like) + 5
...
>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00     8
2000-01-01 00:03:00    17
2000-01-01 00:06:00    26
Freq: 3T, dtype: int64
```

For a Series with a PeriodIndex, the keyword *convention* can be used to control whether to use the start or end of *rule*.

Resample a year by quarter using 'start' *convention*. Values are assigned to the first quarter of the period.

```
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01',
...                                             freq='A',
...                                             periods=2))
>>> s
2012    1
2013    2
Freq: A-DEC, dtype: int64
>>> s.resample('Q', convention='start').asfreq()
2012Q1    1.0
2012Q2    NaN
2012Q3    NaN
2012Q4    NaN
2013Q1    2.0
2013Q2    NaN
2013Q3    NaN
2013Q4    NaN
Freq: Q-DEC, dtype: float64
```

Resample quarters by month using 'end' *convention*. Values are assigned to the last month of the period.

```
>>> q = pd.Series([1, 2, 3, 4], index=pd.period_range('2018-01-01',
...                                                   freq='Q',
...                                                   periods=4))
>>> q
2018Q1    1
2018Q2    2
2018Q3    3
2018Q4    4
Freq: Q-DEC, dtype: int64
>>> q.resample('M', convention='end').asfreq()
2018-03    1.0
2018-04    NaN
2018-05    NaN
2018-06    2.0
2018-07    NaN
2018-08    NaN
2018-09    3.0
2018-10    NaN
2018-11    NaN
2018-12    4.0
Freq: M, dtype: float64
```

For DataFrame objects, the keyword *on* can be used to specify the column instead of the index for resampling.

```
>>> d = {'price': [10, 11, 9, 13, 14, 18, 17, 19],
...      'volume': [50, 60, 40, 100, 50, 100, 40, 50]}
>>> df = pd.DataFrame(d)
>>> df['week_starting'] = pd.date_range('01/01/2018',
...                                     periods=8,
...                                     freq='W')
>>> df
   price  volume week_starting
```

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```
0     10      50    2018-01-07
1     11      60    2018-01-14
2      9      40    2018-01-21
3     13     100    2018-01-28
4     14      50    2018-02-04
5     18     100    2018-02-11
6     17      40    2018-02-18
7     19      50    2018-02-25
>>> df.resample('M', on='week_starting').mean()
               price  volume
week_starting
2018-01-31     10.75    62.5
2018-02-28     17.00    60.0
```

For a DataFrame with MultiIndex, the keyword *level* can be used to specify on which level the resampling needs to take place.

```
>>> days = pd.date_range('1/1/2000', periods=4, freq='D')
>>> d2 = {'price': [10, 11, 9, 13, 14, 18, 17, 19],
...       'volume': [50, 60, 40, 100, 50, 100, 40, 50]}
>>> df2 = pd.DataFrame(d2,
...                    index=pd.MultiIndex.from_product([days,
...                                                      ['morning',
...                                                       'afternoon']]
...                                                     ))
>>> df2
                     price  volume
2000-01-01 morning       10      50
           afternoon     11      60
2000-01-02 morning        9      40
           afternoon     13     100
2000-01-03 morning       14      50
           afternoon     18     100
2000-01-04 morning       17      40
           afternoon     19      50
>>> df2.resample('D', level=0).sum()
            price  volume
2000-01-01     21     110
2000-01-02     22     140
2000-01-03     32     150
2000-01-04     36      90
```

If you want to adjust the start of the bins based on a fixed timestamp:

```
>>> start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'
>>> rng = pd.date_range(start, end, freq='7min')
>>> ts = pd.Series(np.arange(len(rng)) * 3, index=rng)
>>> ts
2000-10-01 23:30:00     0
2000-10-01 23:37:00     3
2000-10-01 23:44:00     6
2000-10-01 23:51:00     9
2000-10-01 23:58:00    12
2000-10-02 00:05:00    15
2000-10-02 00:12:00    18
2000-10-02 00:19:00    21
```

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```
2000-10-02 00:26:00    24
Freq: 7T, dtype: int64
```

```
>>> ts.resample('17min').sum()
2000-10-01 23:14:00     0
2000-10-01 23:31:00     9
2000-10-01 23:48:00    21
2000-10-02 00:05:00    54
2000-10-02 00:22:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.resample('17min', origin='epoch').sum()
2000-10-01 23:18:00     0
2000-10-01 23:35:00    18
2000-10-01 23:52:00    27
2000-10-02 00:09:00    39
2000-10-02 00:26:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.resample('17min', origin='2000-01-01').sum()
2000-10-01 23:24:00     3
2000-10-01 23:41:00    15
2000-10-01 23:58:00    45
2000-10-02 00:15:00    45
Freq: 17T, dtype: int64
```

If you want to adjust the start of the bins with an *offset* Timedelta, the two following lines are equivalent:

```
>>> ts.resample('17min', origin='start').sum()
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.resample('17min', offset='23h30min').sum()
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

To replace the use of the deprecated *base* argument, you can now use *offset*, in this example it is equivalent to have *base=2*:

```
>>> ts.resample('17min', offset='2min').sum()
2000-10-01 23:16:00     0
2000-10-01 23:33:00     9
2000-10-01 23:50:00    36
2000-10-02 00:07:00    39
2000-10-02 00:24:00    24
Freq: 17T, dtype: int64
```

To replace the use of the deprecated *loffset* argument:

```
>>> from pandas.tseries.frequencies import to_offset
>>> loffset = '19min'
>>> ts_out = ts.resample('17min').sum()
>>> ts_out.index = ts_out.index + to_offset(loffset)
>>> ts_out
2000-10-01 23:33:00     0
2000-10-01 23:50:00     9
2000-10-02 00:07:00    21
2000-10-02 00:24:00    54
2000-10-02 00:41:00    24
Freq: 17T, dtype: int64
```

pandas.Series.reset_index

Series.**reset_index**(*level=None*, *drop=False*, *name=None*, *inplace=False*)

Generate a new DataFrame or Series with the index reset.

This is useful when the index needs to be treated as a column, or when the index is meaningless and needs to be reset to the default before another operation.

Parameters

level [int, str, tuple, or list, default optional] For a Series with a MultiIndex, only remove the specified levels from the index. Removes all levels by default.

drop [bool, default False] Just reset the index, without inserting it as a column in the new DataFrame.

name [object, optional] The name to use for the column containing the original Series values. Uses `self.name` by default. This argument is ignored when *drop* is True.

inplace [bool, default False] Modify the Series in place (do not create a new object).

Returns

Series or DataFrame or None When *drop* is False (the default), a DataFrame is returned. The newly created columns will come first in the DataFrame, followed by the original Series values. When *drop* is True, a *Series* is returned. In either case, if `inplace=True`, no value is returned.

See also:

DataFrame.reset_index Analogous function for DataFrame.

Examples

```
>>> s = pd.Series([1, 2, 3, 4], name='foo',
...               index=pd.Index(['a', 'b', 'c', 'd'], name='idx'))
```

Generate a DataFrame with default index.

```
>>> s.reset_index()
  idx  foo
0   a    1
1   b    2
2   c    3
3   d    4
```

To specify the name of the new column use *name*.

```
>>> s.reset_index(name='values')
  idx  values
0   a       1
1   b       2
2   c       3
3   d       4
```

To generate a new Series with the default set *drop* to True.

```
>>> s.reset_index(drop=True)
0    1
1    2
2    3
3    4
Name: foo, dtype: int64
```

To update the Series in place, without generating a new one set *inplace* to True. Note that it also requires `drop=True`.

```
>>> s.reset_index(inplace=True, drop=True)
>>> s
0    1
1    2
2    3
3    4
Name: foo, dtype: int64
```

The *level* parameter is interesting for Series with a multi-level index.

```
>>> arrays = [np.array(['bar', 'bar', 'baz', 'baz']),
...           np.array(['one', 'two', 'one', 'two'])]
>>> s2 = pd.Series(
...     range(4), name='foo',
...     index=pd.MultiIndex.from_arrays(arrays,
...                                     names=['a', 'b']))
```

To remove a specific level from the Index, use *level*.

```
>>> s2.reset_index(level='a')
       a  foo
b
one  bar    0
two  bar    1
one  baz    2
two  baz    3
```

If *level* is not set, all levels are removed from the Index.

```
>>> s2.reset_index()
     a    b  foo
0  bar  one    0
1  bar  two    1
2  baz  one    2
3  baz  two    3
```

pandas.Series.rfloordiv

Series.**rfloordiv**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Integer division of series and other, element-wise (binary operator *rfloordiv*).

Equivalent to `other // series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.floordiv Element-wise Integer division, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.floordiv(b, fill_value=0)
a    1.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

pandas.Series.rmod

Series.**rmod**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Modulo of series and other, element-wise (binary operator *rmod*).

Equivalent to `other % series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.mod Element-wise Modulo, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.mod(b, fill_value=0)
a    0.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

pandas.Series.rmul

Series.**rmul**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Multiplication of series and other, element-wise (binary operator *rmul*).

Equivalent to `other * series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.mul Element-wise Multiplication, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.multiply(b, fill_value=0)
a    1.0
b    0.0
c    0.0
d    0.0
e    NaN
dtype: float64
```

pandas.Series.rolling

Series.**rolling**(*window*, *min_periods=None*, *center=False*, *win_type=None*, *on=None*, *axis=0*, *closed=None*)

Provide rolling window calculations.

Parameters

window [int, offset, or BaseIndexer subclass] Size of the moving window. This is the number of observations used for calculating the statistic. Each window will be a fixed size.

If its an offset then this will be the time period of each window. Each window will be a variable sized based on the observations included in the time-period. This is only valid for datetimelike indexes.

If a BaseIndexer subclass is passed, calculates the window boundaries based on the defined `get_window_bounds` method. Additional rolling keyword arguments, namely *min_periods*, *center*, and *closed* will be passed to *get_window_bounds*.

min_periods [int, default None] Minimum number of observations in window required to have a value (otherwise result is NA). For a window that is specified by an offset, *min_periods* will default to 1. Otherwise, *min_periods* will default to the size of the window.

center [bool, default False] Set the labels at the center of the window.

win_type [str, default None] Provide a window type. If `None`, all points are evenly weighted. See the notes below for further information.

on [str, optional] For a DataFrame, a datetime-like column or MultiIndex level on which to calculate the rolling window, rather than the DataFrame's index. Provided integer column is ignored and excluded from result since an integer index is not used to calculate the rolling window.

axis [int or str, default 0]

closed [str, default None] Make the interval closed on the 'right', 'left', 'both' or 'neither' endpoints. Defaults to 'right'.

Changed in version 1.2.0: The closed parameter with fixed windows is now supported.

Returns

a Window or Rolling sub-classed for the particular operation

See also:

expanding Provides expanding transformations.

ewm Provides exponential weighted functions.

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

To learn more about the offsets & frequency strings, please see this link.

If `win_type=None`, all points are evenly weighted; otherwise, `win_type` can accept a string of any scipy.signal window function.

Certain Scipy window types require additional parameters to be passed in the aggregation function. The additional parameters must match the keywords specified in the Scipy window type method signature. Please see the third example below on how to add the additional parameters.

Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

Rolling sum with a window length of 2, using the 'triang' window type.

```
>>> df.rolling(2, win_type='triang').sum()
     B
0  NaN
1  0.5
2  1.5
3  NaN
4  NaN
```

Rolling sum with a window length of 2, using the 'gaussian' window type (note how we need to specify std).

```
>>> df.rolling(2, win_type='gaussian').sum(std=3)
          B
0       NaN
1  0.986207
2  2.958621
3       NaN
4       NaN
```

Rolling sum with a window length of 2, min_periods defaults to the window length.

```
>>> df.rolling(2).sum()
     B
0  NaN
1  1.0
2  3.0
3  NaN
4  NaN
```

Same as above, but explicitly set the min_periods

```
>>> df.rolling(2, min_periods=1).sum()
     B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0
```

Same as above, but with forward-looking windows

```
>>> indexer = pd.api.indexers.FixedForwardWindowIndexer(window_size=2)
>>> df.rolling(window=indexer, min_periods=1).sum()
     B
0  1.0
1  3.0
2  2.0
3  4.0
4  4.0
```

A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
...                   index = [pd.Timestamp('20130101 09:00:00'),
...                            pd.Timestamp('20130101 09:00:02'),
...                            pd.Timestamp('20130101 09:00:03'),
...                            pd.Timestamp('20130101 09:00:05'),
...                            pd.Timestamp('20130101 09:00:06')])
```

```
>>> df
                       B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min_periods is 1.

```
>>> df.rolling('2s').sum()
                       B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

pandas.Series.round

Series.**round**(*decimals=0*, **args*, ***kwargs*)

Round each value in a Series to the given number of decimals.

Parameters

decimals [int, default 0] Number of decimal places to round to. If decimals is negative, it specifies the number of positions to the left of the decimal point.

***args, **kwargs** Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series Rounded values of the Series.

See also:

numpy.around Round values of an np.array.

DataFrame.round Round values of a DataFrame.

Examples

```
>>> s = pd.Series([0.1, 1.3, 2.7])
>>> s.round()
0    0.0
1    1.0
2    3.0
dtype: float64
```

pandas.Series.rpow

Series.**rpow**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Exponential power of series and other, element-wise (binary operator *rpow*).

Equivalent to `other ** series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.pow Element-wise Exponential power, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.pow(b, fill_value=0)
a    1.0
b    1.0
c    1.0
d    0.0
e    NaN
dtype: float64
```

pandas.Series.rsub

Series.**rsub**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Subtraction of series and other, element-wise (binary operator *rsub*).

Equivalent to `other - series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.sub Element-wise Subtraction, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.subtract(b, fill_value=0)
a    0.0
b    1.0
c    1.0
d   -1.0
e    NaN
dtype: float64
```

pandas.Series.rtruediv

Series.**rtruediv**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Floating division of series and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.truediv Element-wise Floating division, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
d    0.0
e    NaN
dtype: float64
```

pandas.Series.sample

Series.**sample**(*n=None*, *frac=None*, *replace=False*, *weights=None*, *random_state=None*, *axis=None*)

Return a random sample of items from an axis of object.

You can use *random_state* for reproducibility.

Parameters

n [int, optional] Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac [float, optional] Fraction of axis items to return. Cannot be used with *n*.

replace [bool, default False] Allow or disallow sampling of the same row more than once.

weights [str or ndarray-like, optional] Default 'None' results in equal probability weighting. If passed a Series, will align with target object on index. Index values in weights not found in sampled object will be ignored and index values in sampled object not in weights will be assigned weights of zero. If called on a DataFrame, will accept the name of a column when axis = 0. Unless weights are a Series, weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. Infinite values not allowed.

random_state [int, array-like, BitGenerator, np.random.RandomState, optional] If int, array-like, or BitGenerator (NumPy>=1.17), seed for random number generator If np.random.RandomState, use as numpy RandomState object.

Changed in version 1.1.0: array-like and BitGenerator (for NumPy>=1.17) object now passed to np.random.RandomState() as seed

axis [{0 or 'index', 1 or 'columns', None}, default None] Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames).

Returns

Series or DataFrame A new object of same type as caller containing *n* items randomly sampled from the caller object.

See also:

`DataFrameGroupBy.sample` Generates random samples from each group of a DataFrame object.

`SeriesGroupBy.sample` Generates random samples from each group of a Series object.

`numpy.random.choice` Generates a random sample from a given 1-D numpy array.

Notes

If *frac* > 1, *replacement* should be set to *True*.

Examples

```
>>> df = pd.DataFrame({'num_legs': [2, 4, 8, 0],
...                    'num_wings': [2, 0, 0, 0],
...                    'num_specimen_seen': [10, 2, 1, 8]},
...                   index=['falcon', 'dog', 'spider', 'fish'])
>>> df
        num_legs  num_wings  num_specimen_seen
falcon         2          2                 10
dog            4          0                  2
spider         8          0                  1
fish           0          0                  8
```

Extract 3 random elements from the `Series` `df['num_legs']`: Note that we use *random_state* to ensure the reproducibility of the examples.

```
>>> df['num_legs'].sample(n=3, random_state=1)
fish      0
spider    8
falcon    2
Name: num_legs, dtype: int64
```

A random 50% sample of the `DataFrame` with replacement:

```
>>> df.sample(frac=0.5, replace=True, random_state=1)
      num_legs  num_wings  num_specimen_seen
dog          4          0                  2
fish         0          0                  8
```

An upsample sample of the `DataFrame` with replacement: Note that *replace* parameter has to be *True* for *frac* parameter > 1.

```
>>> df.sample(frac=2, replace=True, random_state=1)
        num_legs  num_wings  num_specimen_seen
dog            4          0                  2
fish           0          0                  8
falcon         2          2                 10
falcon         2          2                 10
fish           0          0                  8
```

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```
dog             4           0                   2
fish            0           0                   8
dog             4           0                   2
```

Using a DataFrame column as weights. Rows with larger value in the *num_specimen_seen* column are more likely to be sampled.

```
>>> df.sample(n=2, weights='num_specimen_seen', random_state=1)
        num_legs  num_wings  num_specimen_seen
falcon         2          2                 10
fish           0          0                  8
```

pandas.Series.searchsorted

`Series.`**`searchsorted`**(*value*, *side='left'*, *sorter=None*)

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series *self* such that, if the corresponding elements in *value* were inserted before the indices, the order of *self* would be preserved.

Note: The Series *must* be monotonically sorted, otherwise wrong locations will likely be returned. Pandas does *not* check this for you.

Parameters

value [array_like] Values to insert into *self*.

side [{'left', 'right'}, optional] If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *self*).

sorter [1-D array_like, optional] Optional array of integer indices that sort *self* into ascending order. They are typically the result of `np.argsort`.

Returns

int or array of int A scalar or array of insertion points with the same shape as *value*.

Changed in version 0.24.0: If *value* is a scalar, an int is now always returned. Previously, scalar inputs returned an 1-item array for *Series* and *Categorical*.

See also:

sort_values Sort by the values along either axis.

numpy.searchsorted Similar method from NumPy.

Notes

Binary search is used to find the required insertion points.

Examples

```
>>> ser = pd.Series([1, 2, 3])
>>> ser
0    1
1    2
2    3
dtype: int64
```

```
>>> ser.searchsorted(4)
3
```

```
>>> ser.searchsorted([0, 4])
array([0, 3])
```

```
>>> ser.searchsorted([1, 3], side='left')
array([0, 2])
```

```
>>> ser.searchsorted([1, 3], side='right')
array([1, 3])
```

```
>>> ser = pd.Series(pd.to_datetime(['3/11/2000', '3/12/2000', '3/13/2000']))
>>> ser
0   2000-03-11
1   2000-03-12
2   2000-03-13
dtype: datetime64[ns]
```

```
>>> ser.searchsorted('3/14/2000')
3
```

```
>>> ser = pd.Categorical(
...     ['apple', 'bread', 'bread', 'cheese', 'milk'], ordered=True
... )
>>> ser
['apple', 'bread', 'bread', 'cheese', 'milk']
Categories (4, object): ['apple' < 'bread' < 'cheese' < 'milk']
```

```
>>> ser.searchsorted('bread')
1
```

```
>>> ser.searchsorted(['bread'], side='right')
array([3])
```

If the values are not monotonically sorted, wrong locations may be returned:

```
>>> ser = pd.Series([2, 1, 3])
>>> ser
0    2
```

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```
1    1
2    3
dtype: int64
```

```
>>> ser.searchsorted(1)
0  # wrong result, correct would be 1
```

pandas.Series.sem

Series.**sem**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis [{index (0)}]

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

scalar or Series (if level specified)

Notes

To have the same behaviour as *numpy.std*, use *ddof=0* (instead of the default *ddof=1*)

pandas.Series.set_axis

Series.**set_axis**(*labels*, *axis=0*, *inplace=False*)

Assign desired index to given axis.

Indexes for row labels can be changed by assigning a list-like or Index.

Parameters

labels [list-like, Index] The values for the new index.

axis [{0 or 'index'}, default 0] The axis to update. The value 0 identifies the rows.

inplace [bool, default False] Whether to return a new Series instance.

Returns

renamed [Series or None] An object of type Series or None if `inplace=True`.

See also:

Series.rename_axis Alter the name of the index.

Examples

```
>>> s = pd.Series([1, 2, 3])
>>> s
0    1
1    2
2    3
dtype: int64
```

```
>>> s.set_axis(['a', 'b', 'c'], axis=0)
a    1
b    2
c    3
dtype: int64
```

pandas.Series.set_flags

Series.**set_flags**(*, *copy=False*, *allows_duplicate_labels=None*)

Return a new object with updated flags.

Parameters

allows_duplicate_labels [bool, optional] Whether the returned object allows duplicate labels.

Returns

Series or DataFrame The same type as the caller.

See also:

DataFrame.attrs Global metadata applying to this dataset.

DataFrame.flags Global flags applying to this object.

Notes

This method returns a new object that's a view on the same data as the input. Mutating the input or the output values will be reflected in the other.

This method is intended to be used in method chains.

"Flags" differ from "metadata". Flags reflect properties of the pandas object (the Series or DataFrame). Metadata refer to properties of the dataset, and should be stored in *DataFrame.attrs*.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2]})
>>> df.flags.allows_duplicate_labels
True
>>> df2 = df.set_flags(allows_duplicate_labels=False)
>>> df2.flags.allows_duplicate_labels
False
```

pandas.Series.shift

Series.**shift**(*periods=1*, *freq=None*, *axis=0*, *fill_value=None*)

Shift index by desired number of periods with an optional time *freq*.

When *freq* is not passed, shift the index without realigning the data. If *freq* is passed (in this case, the index must be date or datetime, or it will raise a *NotImplementedError*), the index will be increased using the periods and the *freq*. *freq* can be inferred when specified as "infer" as long as either freq or inferred_freq attribute is set in the index.

Parameters

periods [int] Number of periods to shift. Can be positive or negative.

freq [DateOffset, tseries.offsets, timedelta, or str, optional] Offset to use from the tseries module or time rule (e.g. 'EOM'). If *freq* is specified then the index values are shifted but the data is not realigned. That is, use *freq* if you would like to extend the index when shifting and preserve the original data. If *freq* is specified as "infer" then it will be inferred from the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown.

axis [{0 or 'index', 1 or 'columns', None}, default None] Shift direction.

fill_value [object, optional] The scalar value to use for newly introduced missing values. the default depends on the dtype of *self*. For numeric data, `np.nan` is used. For datetime, timedelta, or period data, etc. `NaT` is used. For extension dtypes, `self.dtype.na_value` is used.

Changed in version 1.1.0.

Returns

Series Copy of input object, shifted.

See also:

Index.shift Shift values of Index.

DatetimeIndex.shift Shift values of DatetimeIndex.

PeriodIndex.shift Shift values of PeriodIndex.

tshift Shift the time index, using the index's frequency if available.

Examples

```
>>> df = pd.DataFrame({"Col1": [10, 20, 15, 30, 45],
...                    "Col2": [13, 23, 18, 33, 48],
...                    "Col3": [17, 27, 22, 37, 52]},
...                   index=pd.date_range("2020-01-01", "2020-01-05"))
>>> df
            Col1  Col2  Col3
2020-01-01    10    13    17
2020-01-02    20    23    27
2020-01-03    15    18    22
2020-01-04    30    33    37
2020-01-05    45    48    52
```

```
>>> df.shift(periods=3)
            Col1  Col2  Col3
2020-01-01   NaN   NaN   NaN
2020-01-02   NaN   NaN   NaN
2020-01-03   NaN   NaN   NaN
2020-01-04  10.0  13.0  17.0
2020-01-05  20.0  23.0  27.0
```

```
>>> df.shift(periods=1, axis="columns")
            Col1  Col2  Col3
2020-01-01   NaN    10    13
2020-01-02   NaN    20    23
2020-01-03   NaN    15    18
2020-01-04   NaN    30    33
2020-01-05   NaN    45    48
```

```
>>> df.shift(periods=3, fill_value=0)
            Col1  Col2  Col3
2020-01-01     0     0     0
2020-01-02     0     0     0
2020-01-03     0     0     0
2020-01-04    10    13    17
2020-01-05    20    23    27
```

```
>>> df.shift(periods=3, freq="D")
            Col1  Col2  Col3
2020-01-04    10    13    17
2020-01-05    20    23    27
2020-01-06    15    18    22
2020-01-07    30    33    37
2020-01-08    45    48    52
```

```
>>> df.shift(periods=3, freq="infer")
            Col1  Col2  Col3
2020-01-04    10    13    17
2020-01-05    20    23    27
2020-01-06    15    18    22
2020-01-07    30    33    37
2020-01-08    45    48    52
```

pandas.Series.skew

Series.**skew**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased skew over requested axis.

Normalized by N-1.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

pandas.Series.slice_shift

Series.**slice_shift**(*periods=1*, *axis=0*)

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Deprecated since version 1.2.0: slice_shift is deprecated, use DataFrame/Series.shift instead.

Parameters

periods [int] Number of periods to move, can be positive or negative.

Returns

shifted [same type as caller]

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.Series.sort_index

Series.**sort_index**(*axis=0*, *level=None*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*, *sort_remaining=True*, *ignore_index=False*, *key=None*)

Sort Series by index labels.

Returns a new Series sorted by label if *inplace* argument is `False`, otherwise updates the original series and returns None.

Parameters

axis [int, default 0] Axis to direct sorting. This can only be 0 for Series.

level [int, optional] If not None, sort on values in specified index level(s).

ascending [bool or list of bools, default True] Sort ascending vs. descending. When the index is a MultiIndex the sort direction can be controlled for each level individually.

inplace [bool, default False] If True, perform operation in-place.

kind [{'quicksort', 'mergesort', 'heapsort'}, default 'quicksort'] Choice of sorting algorithm. See also `numpy.sort()` for more information. 'mergesort' is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

na_position [{'first', 'last'}, default 'last'] If 'first' puts NaNs at the beginning, 'last' puts NaNs at the end. Not implemented for MultiIndex.

sort_remaining [bool, default True] If True and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level.

ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, . . . , n - 1.

New in version 1.0.0.

key [callable, optional] If not None, apply the key function to the index values before sorting. This is similar to the *key* argument in the builtin `sorted()` function, with the notable difference that this *key* function should be *vectorized*. It should expect an `Index` and return an `Index` of the same shape.

New in version 1.1.0.

Returns

Series or None The original Series sorted by the labels or None if `inplace=True`.

See also:

DataFrame.sort_index Sort DataFrame by the index.

DataFrame.sort_values Sort DataFrame by the value.

Series.sort_values Sort Series by the value.

Examples

```
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, 4])
>>> s.sort_index()
1    c
2    b
3    a
4    d
dtype: object
```

Sort Descending

```
>>> s.sort_index(ascending=False)
4    d
3    a
2    b
1    c
dtype: object
```

Sort Inplace

```
>>> s.sort_index(inplace=True)
>>> s
1    c
2    b
3    a
4    d
dtype: object
```

By default NaNs are put at the end, but use *na_position* to place them at the beginning

```
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, np.nan])
>>> s.sort_index(na_position='first')
NaN     d
 1.0    c
 2.0    b
 3.0    a
dtype: object
```

Specify index level to sort

```
>>> arrays = [np.array(['qux', 'qux', 'foo', 'foo',
...                     'baz', 'baz', 'bar', 'bar']),
...           np.array(['two', 'one', 'two', 'one',
...                     'two', 'one', 'two', 'one'])]
>>> s = pd.Series([1, 2, 3, 4, 5, 6, 7, 8], index=arrays)
>>> s.sort_index(level=1)
bar  one    8
baz  one    6
foo  one    4
qux  one    2
bar  two    7
baz  two    5
foo  two    3
qux  two    1
dtype: int64
```

Does not sort by remaining levels when sorting by levels

```
>>> s.sort_index(level=1, sort_remaining=False)
qux  one    2
foo  one    4
baz  one    6
bar  one    8
qux  two    1
foo  two    3
baz  two    5
bar  two    7
dtype: int64
```

Apply a key function before sorting

```
>>> s = pd.Series([1, 2, 3, 4], index=['A', 'b', 'C', 'd'])
>>> s.sort_index(key=lambda x : x.str.lower())
A    1
b    2
C    3
d    4
dtype: int64
```

pandas.Series.sort_values

Series.**sort_values**(*axis=0*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*, *ignore_index=False*, *key=None*)

Sort by the values.

Sort a Series in ascending or descending order by some criterion.

Parameters

axis [{0 or 'index'}, default 0] Axis to direct sorting. The value 'index' is accepted for compatibility with DataFrame.sort_values.

ascending [bool, default True] If True, sort values in ascending order, otherwise descending.

inplace [bool, default False] If True, perform operation in-place.

kind [{'quicksort', 'mergesort' or 'heapsort'}, default 'quicksort'] Choice of sorting algorithm. See also `numpy.sort()` for more information. 'mergesort' is the only stable algorithm.

na_position [{'first' or 'last'}, default 'last'] Argument 'first' puts NaNs at the beginning, 'last' puts NaNs at the end.

ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, . . . , n - 1.

New in version 1.0.0.

key [callable, optional] If not None, apply the key function to the series values before sorting. This is similar to the *key* argument in the builtin `sorted()` function, with the notable difference that this *key* function should be *vectorized*. It should expect a `Series` and return an array-like.

New in version 1.1.0.

Returns

Series or None Series ordered by values or None if `inplace=True`.

See also:

Series.sort_index Sort by the Series indices.

DataFrame.sort_values Sort DataFrame by the values along either axis.

DataFrame.sort_index Sort DataFrame by indices.

Examples

```
>>> s = pd.Series([np.nan, 1, 3, 10, 5])
>>> s
0     NaN
1     1.0
2     3.0
3     10.0
4     5.0
dtype: float64
```

Sort values ascending order (default behaviour)

```
>>> s.sort_values(ascending=True)
1     1.0
2     3.0
4     5.0
3    10.0
0     NaN
dtype: float64
```

Sort values descending order

```
>>> s.sort_values(ascending=False)
3    10.0
4     5.0
2     3.0
1     1.0
0     NaN
dtype: float64
```

Sort values inplace

```
>>> s.sort_values(ascending=False, inplace=True)
>>> s
3    10.0
4     5.0
2     3.0
1     1.0
0     NaN
dtype: float64
```

Sort values putting NAs first

```
>>> s.sort_values(na_position='first')
0     NaN
1     1.0
2     3.0
4     5.0
3    10.0
dtype: float64
```

Sort a series of strings

```
>>> s = pd.Series(['z', 'b', 'd', 'a', 'c'])
>>> s
0    z
1    b
2    d
3    a
4    c
dtype: object
```

```
>>> s.sort_values()
3    a
1    b
4    c
2    d
0    z
dtype: object
```

Sort using a key function. Your *key* function will be given the `Series` of values and should return an array-like.

```
>>> s = pd.Series(['a', 'B', 'c', 'D', 'e'])
>>> s.sort_values()
1    B
3    D
0    a
2    c
4    e
dtype: object
>>> s.sort_values(key=lambda x: x.str.lower())
0    a
1    B
2    c
3    D
4    e
dtype: object
```

NumPy ufuncs work well here. For example, we can sort by the `sin` of the value

```
>>> s = pd.Series([-4, -2, 0, 2, 4])
>>> s.sort_values(key=np.sin)
1   -2
4    4
2    0
0   -4
3    2
dtype: int64
```

More complicated user-defined functions can be used, as long as they expect a Series and return an array-like

```
>>> s.sort_values(key=lambda x: (np.tan(x.cumsum())))
0   -4
3    2
4    4
1   -2
2    0
dtype: int64
```

pandas.Series.sparse

`Series.`**`sparse`**`()`
Accessor for SparseSparse from other sparse matrix data types.

pandas.Series.squeeze

Series.**squeeze**(*axis=None*)

Squeeze 1 dimensional axis objects into scalars.

Series or DataFrames with a single element are squeezed to a scalar. DataFrames with a single column or a single row are squeezed to a Series. Otherwise the object is unchanged.

This method is most useful when you don't know if your object is a Series or DataFrame, but you do know it has just a single column. In that case you can safely call *squeeze* to ensure you have a Series.

Parameters

axis [{0 or 'index', 1 or 'columns', None}, default None] A specific axis to squeeze. By default, all length-1 axes are squeezed.

Returns

DataFrame, Series, or scalar The projection after squeezing *axis* or all the axes.

See also:

Series.iloc Integer-location based indexing for selecting scalars.

DataFrame.iloc Integer-location based indexing for selecting Series.

Series.to_frame Inverse of DataFrame.squeeze for a single-column DataFrame.

Examples

```
>>> primes = pd.Series([2, 3, 5, 7])
```

Slicing might produce a Series with a single value:

```
>>> even_primes = primes[primes % 2 == 0]
>>> even_primes
0    2
dtype: int64
```

```
>>> even_primes.squeeze()
2
```

Squeezing objects with more than one value in every axis does nothing:

```
>>> odd_primes = primes[primes % 2 == 1]
>>> odd_primes
1    3
2    5
3    7
dtype: int64
```

```
>>> odd_primes.squeeze()
1    3
2    5
3    7
dtype: int64
```

Squeezing is even more effective when used with DataFrames.

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=['a', 'b'])
>>> df
   a  b
0  1  2
1  3  4
```

Slicing a single column will produce a DataFrame with the columns having only one value:

```
>>> df_a = df[['a']]
>>> df_a
   a
0  1
1  3
```

So the columns can be squeezed down, resulting in a Series:

```
>>> df_a.squeeze('columns')
0    1
1    3
Name: a, dtype: int64
```

Slicing a single row from a single column will produce a single scalar DataFrame:

```
>>> df_0a = df.loc[df.index < 1, ['a']]
>>> df_0a
   a
0  1
```

Squeezing the rows produces a single scalar Series:

```
>>> df_0a.squeeze('rows')
a    1
Name: 0, dtype: int64
```

Squeezing all axes will project directly into a scalar:

```
>>> df_0a.squeeze()
1
```

pandas.Series.std

Series.**std**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return sample standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis [{index (0)}]

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

scalar or Series (if level specified)

Notes

To have the same behaviour as *numpy.std*, use *ddof=0* (instead of the default *ddof=1*)

pandas.Series.str

`Series.str()`

Vectorized string functions for Series and Index.

NAs stay NA unless handled otherwise by a particular method. Patterned after Python's string methods, with some inspiration from R's stringr package.

Examples

```
>>> s = pd.Series(["A_Str_Series"])
>>> s
0    A_Str_Series
dtype: object
```

```
>>> s.str.split("_")
0    [A, Str, Series]
dtype: object
```

```
>>> s.str.replace("_", "")
0    AStrSeries
dtype: object
```

pandas.Series.sub

`Series.sub(`*other*, *level=None*, *fill_value=None*, *axis=0*`)`

Return Subtraction of series and other, element-wise (binary operator *sub*).

Equivalent to `series - other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rsub Reverse of the Subtraction operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.subtract(b, fill_value=0)
a    0.0
b    1.0
c    1.0
d   -1.0
e    NaN
dtype: float64
```

pandas.Series.subtract

Series.**subtract**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Subtraction of series and other, element-wise (binary operator *sub*).

Equivalent to `series - other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rsub Reverse of the Subtraction operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.subtract(b, fill_value=0)
a    0.0
b    1.0
c    1.0
d   -1.0
e    NaN
dtype: float64
```

pandas.Series.sum

Series.**sum**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, *min_count=0*, ***kwargs*)

Return the sum of the values over the requested axis.

This is equivalent to the method `numpy.sum`.

Parameters

axis [{index (0)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded  animal
warm     dog       4
         falcon    2
cold     fish      0
         spider    8
Name: legs, dtype: int64
```

```
>>> s.sum()
14
```

Sum using level names, as well as indices.

```
>>> s.sum(level='blooded')
blooded
warm    6
cold    8
Name: legs, dtype: int64
```

```
>>> s.sum(level=0)
blooded
warm    6
cold    8
Name: legs, dtype: int64
```

By default, the sum of an empty or all-NA Series is `0`.

```
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the `min_count` parameter. For example, if you'd like the sum of an empty series to be NaN, pass `min_count=1`.

```
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).sum()
0.0
```

```
>>> pd.Series([np.nan]).sum(min_count=1)
nan
```

pandas.Series.swapaxes

`Series.`**`swapaxes`**(*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately.

Returns

y [same as input]

pandas.Series.swaplevel

`Series.`**`swaplevel`**(*i=- 2*, *j=- 1*, *copy=True*)

Swap levels i and j in a *MultiIndex*.

Default is to swap the two innermost levels of the index.

Parameters

i, j [int, str] Level of the indices to be swapped. Can pass level name as string.

copy [bool, default True] Whether to copy underlying data.

Returns

Series Series with levels swapped in MultiIndex.

pandas.Series.tail

`Series.`**`tail`**(*n=5*)

Return the last *n* rows.

This function returns last *n* rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.

For negative values of *n*, this function returns all rows except the first *n* rows, equivalent to `df[n:]`.

Parameters

n [int, default 5] Number of rows to select.

Returns

type of caller The last *n* rows of the caller object.

See also:

DataFrame.head The first *n* rows of the caller object.

Examples

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                               'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
5     parrot
6      shark
7      whale
8      zebra
```

Viewing the last 5 lines

```
>>> df.tail()
   animal
4  monkey
5  parrot
6   shark
7   whale
8   zebra
```

Viewing the last *n* lines (three in this case)

```
>>> df.tail(3)
  animal
6  shark
7  whale
8  zebra
```

For negative values of *n*

```
>>> df.tail(-3)
   animal
3    lion
4  monkey
5  parrot
6   shark
7   whale
8   zebra
```

pandas.Series.take

`Series.`**`take`**(*indices*, *axis=0*, *is_copy=None*, ***kwargs*)

Return the elements in the given *positional* indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

Parameters

indices [array-like] An array of ints indicating which positions to take.

axis [{0 or 'index', 1 or 'columns', None}, default 0] The axis on which to select elements. `0` means that we are selecting rows, `1` means that we are selecting columns.

is_copy [bool] Before pandas 1.0, `is_copy=False` can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, `take` always returns a copy, and the keyword is therefore deprecated.

Deprecated since version 1.0.0.

****kwargs** For compatibility with `numpy.take()`. Has no effect on the output.

Returns

taken [same type as caller] An array-like containing the elements taken from the object.

See also:

DataFrame.loc Select a subset of a DataFrame by labels.

DataFrame.iloc Select a subset of a DataFrame by positions.

numpy.take Take elements from an array along an axis.

Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                    ('parrot', 'bird', 24.0),
...                    ('lion', 'mammal', 80.5),
...                    ('monkey', 'mammal', np.nan)],
...                   columns=['name', 'class', 'max_speed'],
...                   index=[0, 2, 3, 1])
>>> df
     name   class  max_speed
0  falcon    bird      389.0
2  parrot    bird       24.0
3    lion  mammal       80.5
1  monkey  mammal        NaN
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```
>>> df.take([0, 3])
     name   class  max_speed
0  falcon    bird      389.0
1  monkey  mammal        NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```
>>> df.take([1, 2], axis=1)
    class  max_speed
0    bird      389.0
2    bird       24.0
3  mammal       80.5
1  mammal        NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```
>>> df.take([-1, -2])
     name   class  max_speed
1  monkey  mammal        NaN
3    lion  mammal       80.5
```

pandas.Series.to_clipboard

Series.**to_clipboard**(*excel=True*, *sep=None*, ***kwargs*)

Copy object to the system clipboard.

Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

Parameters

excel [bool, default True] Produce output in a csv format for easy pasting into excel.

- True, use the provided separator for csv pasting.
- False, write a string representation of the object to the clipboard.

sep [str, default `'\t'`] Field delimiter.

****kwargs** These parameters will be passed to DataFrame.to_csv.

See also:

DataFrame.to_csv Write a DataFrame to a comma-separated values (csv) file.

read_clipboard Read text from clipboard and pass to read_table.

Notes

Requirements for your platform.

- Linux : *xclip*, or *xsel* (with *PyQt4* modules)
- Windows : none
- OS X : none

Examples

Copy the contents of a DataFrame to the clipboard.

```
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
```

```
>>> df.to_clipboard(sep=',')
... # Wrote the following to the system clipboard:
... # ,A,B,C
... # 0,1,2,3
... # 1,4,5,6
```

We can omit the index by passing the keyword *index* and setting it to false.

```
>>> df.to_clipboard(sep=',', index=False)
... # Wrote the following to the system clipboard:
... # A,B,C
... # 1,2,3
... # 4,5,6
```

pandas.Series.to_csv

Series.**to_csv**(*path_or_buf=None*, *sep=','*, *na_rep=''*, *float_format=None*, *columns=None*, *header=True*, *index=True*, *index_label=None*, *mode='w'*, *encoding=None*, *compression='infer'*, *quoting=None*, *quotechar='"'*, *line_terminator=None*, *chunksize=None*, *date_format=None*, *doublequote=True*, *escapechar=None*, *decimal='.'*, *errors='strict'*, *storage_options=None*)

Write object to a comma-separated values (csv) file.

Changed in version 0.24.0: The order of arguments for Series was changed.

Parameters

path_or_buf [str or file handle, default None] File path or object, if None is provided the result is returned as a string. If a non-binary file object is passed, it should be opened with *newline=''*, disabling universal newlines. If a binary file object is passed, *mode* might need to contain a *'b'*.

Changed in version 0.24.0: Was previously named "path" for Series.

Changed in version 1.2.0: Support for binary file objects was introduced.

sep [str, default ','] String of length 1. Field delimiter for the output file.

na_rep [str, default ''] Missing data representation.

float_format [str, default None] Format string for floating point numbers.

columns [sequence, optional] Columns to write.

header [bool or list of str, default True] Write out the column names. If a list of strings is given it is assumed to be aliases for the column names.

Changed in version 0.24.0: Previously defaulted to False for Series.

index [bool, default True] Write row names (index).

index_label [str or sequence, or False, default None] Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the object uses MultiIndex. If False do not print fields for index names. Use index_label=False for easier importing in R.

mode [str] Python write mode, default 'w'.

encoding [str, optional] A string representing the encoding to use in the output file, defaults to 'utf-8'. *encoding* is not supported if *path_or_buf* is a non-binary file object.

compression [str or dict, default 'infer'] If str, represents compression mode. If dict, value at 'method' is the compression mode. Compression mode may be any of the following possible values: {'infer', 'gzip', 'bz2', 'zip', 'xz', None}. If compression mode is 'infer' and *path_or_buf* is path-like, then detect compression mode from the following extensions: '.gz', '.bz2', '.zip' or '.xz'. (otherwise no compression). If dict given and mode is one of {'zip', 'gzip', 'bz2'}, or inferred as one of the above, other entries passed as additional compression options.

Changed in version 1.0.0: May now be a dict with key 'method' as compression mode and other entries as additional compression options if compression mode is 'zip'.

Changed in version 1.1.0: Passing compression options as keys in dict is supported for compression modes 'gzip' and 'bz2' as well as 'zip'.

Changed in version 1.2.0: Compression is supported for binary file objects.

Changed in version 1.2.0: Previous versions forwarded dict entries for 'gzip' to *gzip.open* instead of *gzip.GzipFile* which prevented setting *mtime*.

quoting [optional constant from csv module] Defaults to csv.QUOTE_MINIMAL. If you have set a *float_format* then floats are converted to strings and thus csv.QUOTE_NONNUMERIC will treat them as non-numeric.

quotechar [str, default '"'] String of length 1. Character used to quote fields.

line_terminator [str, optional] The newline character or character sequence to use in the output file. Defaults to *os.linesep*, which depends on the OS in which this method is called ('n' for linux, 'rn' for Windows, i.e.).

Changed in version 0.24.0.

chunksize [int or None] Rows to write at a time.

date_format [str, default None] Format string for datetime objects.

doublequote [bool, default True] Control quoting of *quotechar* inside a field.

escapechar [str, default None] String of length 1. Character used to escape *sep* and *quotechar* when appropriate.

decimal [str, default '.'] Character recognized as decimal separator. E.g. use ',' for European data.

errors [str, default 'strict'] Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.

New in version 1.1.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

None or str If path_or_buf is None, returns the resulting csv format as a string. Otherwise returns None.

See also:

read_csv Load a CSV file into a DataFrame.

to_excel Write DataFrame to an Excel file.

Examples

```
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
...                    'mask': ['red', 'purple'],
...                    'weapon': ['sai', 'bo staff']})
>>> df.to_csv(index=False)
'name,mask,weapon\nRaphael,red,sai\nDonatello,purple,bo staff\n'
```

Create 'out.zip' containing 'out.csv'

```
>>> compression_opts = dict(method='zip',
...                         archive_name='out.csv')
>>> df.to_csv('out.zip', index=False,
...           compression=compression_opts)
```

pandas.Series.to_dict

Series.**to_dict**(*into=<class 'dict'>*)

Convert Series to {label -> value} dict or dict-like object.

Parameters

into [class, default dict] The collections.abc.Mapping subclass to use as the return object. Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.

Returns

collections.abc.Mapping Key-value representation of Series.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_dict()
{0: 1, 1: 2, 2: 3, 3: 4}
>>> from collections import OrderedDict, defaultdict
>>> s.to_dict(OrderedDict)
OrderedDict([(0, 1), (1, 2), (2, 3), (3, 4)])
>>> dd = defaultdict(list)
>>> s.to_dict(dd)
defaultdict(<class 'list'>, {0: 1, 1: 2, 2: 3, 3: 4})
```

pandas.Series.to_excel

Series.**to_excel**(*excel_writer*, *sheet_name='Sheet1'*, *na_rep=''*, *float_format=None*, *columns=None*, *header=True*, *index=True*, *index_label=None*, *startrow=0*, *startcol=0*, *engine=None*, *merge_cells=True*, *encoding=None*, *inf_rep='inf'*, *verbose=True*, *freeze_panes=None*, *storage_options=None*)

Write object to an Excel sheet.

To write a single object to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an *ExcelWriter* object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique *sheet_name*. With all data written to the file it is necessary to save the changes. Note that creating an *ExcelWriter* object with a file name that already exists will result in the contents of the existing file being erased.

Parameters

excel_writer [path-like, file-like, or ExcelWriter object] File path or existing ExcelWriter.

sheet_name [str, default 'Sheet1'] Name of sheet which will contain DataFrame.

na_rep [str, default ''] Missing data representation.

float_format [str, optional] Format string for floating point numbers. For example `float_format="%.2f"` will format 0.1234 to 0.12.

columns [sequence or list of str, optional] Columns to write.

header [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

index_label [str or sequence, optional] Column label for index column(s) if desired. If not specified, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow [int, default 0] Upper left cell row to dump data frame.

startcol [int, default 0] Upper left cell column to dump data frame.

engine [str, optional] Write engine to use, 'openpyxl' or 'xlsxwriter'. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

Deprecated since version 1.2.0: As the xlwt package is no longer maintained, the `xlwt` engine will be removed in a future version of pandas.

merge_cells [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

encoding [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep [str, default 'inf'] Representation for infinity (there is no native representation for infinity in Excel).

verbose [bool, default True] Display more information in the error logs.

freeze_panes [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

See also:

to_csv Write DataFrame to a comma-separated values (csv) file.

ExcelWriter Class for writing DataFrame objects into excel sheets.

read_excel Read an Excel file into a pandas DataFrame.

read_csv Read a comma-separated values (csv) file into DataFrame.

Notes

For compatibility with *to_csv()*, to_excel serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

Examples

Create, write to and save a workbook:

```
>>> df1 = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                    index=['row 1', 'row 2'],
...                    columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```
>>> df1.to_excel("output.xlsx",
...              sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:

```
>>> with pd.ExcelWriter('output.xlsx',
...                     mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the *engine* keyword (the default engine is automatically chosen depending on the file extension):

```
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

pandas.Series.to_frame

Series.**to_frame**(*name=None*)

Convert Series to DataFrame.

Parameters

name [object, default None] The passed name should substitute for the series name (if it has one).

Returns

DataFrame DataFrame representation of Series.

Examples

```
>>> s = pd.Series(["a", "b", "c"],
...               name="vals")
>>> s.to_frame()
  vals
0    a
1    b
2    c
```

pandas.Series.to_hdf

Series.**to_hdf**(*path_or_buf*, *key*, *mode='a'*, *complevel=None*, *complib=None*, *append=False*, *format=None*, *index=True*, *min_itemsize=None*, *nan_rep=None*, *dropna=None*, *data_columns=None*, *errors='strict'*, *encoding='UTF-8'*)

Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different a key.

For more information see the *user guide*.

Parameters

path_or_buf [str or pandas.HDFStore] File path or HDFStore object.

key [str] Identifier for the group in the store.

mode [{'a', 'w', 'r+'}, default 'a'] Mode to open file:

- 'w': write, a new file is created (an existing file with the same name would be deleted).
- 'a': append, an existing file is opened for reading and writing, and if the file does not exist it is created.
- 'r+': similar to 'a', but the file must already exist.

complevel [{0-9}, optional] Specifies a compression level for data. A value of 0 disables compression.

complib [{'zlib', 'lzo', 'bzip2', 'blosc'}, default 'zlib'] Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: 'blosc:blosclz'): {'blosc:blosclz', 'blosc:lz4', 'blosc:lz4hc', 'blosc:snappy', 'blosc:zlib', 'blosc:zstd'}. Specifying a compression library which is not available issues a ValueError.

append [bool, default False] For Table formats, append the input data to the existing.

format [{'fixed', 'table', None}, default 'fixed'] Possible values:

- 'fixed': Fixed format. Fast writing/reading. Not-appendable, nor searchable.

- 'table': Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
- If None, pd.get_option('io.hdf.default_format') is checked, followed by fallback to "fixed"

errors [str, default 'strict'] Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.

encoding [str, default "UTF-8"]

min_itemsize [dict or int, optional] Map column names to minimum string sizes for columns.

nan_rep [Any, optional] How to represent null values as str. Not allowed with append=True.

data_columns [list of columns or True, optional] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See *Query via data columns*. Applicable only to format='table'.

See also:

`DataFrame.read_hdf` Read from HDF file.

`DataFrame.to_parquet` Write a DataFrame to the binary parquet format.

`DataFrame.to_sql` Write to a sql table.

`DataFrame.to_feather` Write out feather-format for DataFrames.

`DataFrame.to_csv` Write out to a csv file.

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},
...                   index=['a', 'b', 'c'])
>>> df.to_hdf('data.h5', key='df', mode='w')
```

We can add another object to the same file:

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```
>>> pd.read_hdf('data.h5', 'df')
A  B
a  1  4
b  2  5
c  3  6
>>> pd.read_hdf('data.h5', 's')
0    1
1    2
2    3
3    4
dtype: int64
```

Deleting file with data:

```
>>> import os
>>> os.remove('data.h5')
```

pandas.Series.to_json

Series.**to_json**(*path_or_buf=None*, *orient=None*, *date_format=None*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*, *lines=False*, *compression='infer'*, *index=True*, *indent=None*, *storage_options=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters

path_or_buf [str or file handle, optional] File path or object. If not specified, the result is returned as a string.

orient [str] Indication of expected JSON string format.

- Series:
  - default is 'index'
  - allowed values are: {'split', 'records', 'index', 'table'}.
- DataFrame:
  - default is 'columns'
  - allowed values are: {'split', 'records', 'index', 'columns', 'values', 'table'}.
- The format of the JSON string:
  - 'split' : dict like {'index' -> [index], 'columns' -> [columns], 'data' -> [values]}
  - 'records' : list like [{column -> value}, ... , {column -> value}]
  - 'index' : dict like {index -> {column -> value}}
  - 'columns' : dict like {column -> {index -> value}}
  - 'values' : just the values array
  - 'table' : dict like {'schema': {schema}, 'data': {data}}

  Describing the data, where data component is like `orient='records'`.

date_format [{None, 'epoch', 'iso'}] Type of date conversion. 'epoch' = epoch milliseconds, 'iso' = ISO8601. The default depends on the *orient*. For `orient='table'`, the default is 'iso'. For all other orients, the default is 'epoch'.

double_precision [int, default 10] The number of decimal places to use when encoding floating point values.

force_ascii [bool, default True] Force encoded string to be ASCII.

date_unit [str, default 'ms' (milliseconds)] The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler [callable, default None] Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

lines [bool, default False] If 'orient' is 'records' write out line delimited json format. Will throw ValueError if incorrect 'orient' since others are not list like.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}] A string representing the compression to use in the output file, only used when the first argument is a filename. By default, the compression is inferred from the filename.

Changed in version 0.24.0: 'infer' option added and set to default

index [bool, default True] Whether to include the index values in the JSON string. Not including the index (`index=False`) is only supported when orient is 'split' or 'table'.

indent [int, optional] Length of whitespace used to indent each record.

New in version 1.0.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

None or str If path_or_buf is None, returns the resulting json format as a string. Otherwise returns None.

See also:

read_json Convert a JSON string to pandas object.

Notes

The behavior of `indent=0` varies from the stdlib, which does not indent the output but does insert newlines. Currently, `indent=0` and the default `indent=None` are equivalent in pandas, though this may change in a future release.

`orient='table'` contains a 'pandas_version' field under 'schema'. This stores the version of *pandas* used in the latest revision of the schema.

Examples

```
>>> import json
>>> df = pd.DataFrame(
...     [["a", "b"], ["c", "d"]],
...     index=["row 1", "row 2"],
...     columns=["col 1", "col 2"],
... )
```

```
>>> result = df.to_json(orient="split")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "columns": [
        "col 1",
        "col 2"
    ],
    "index": [
        "row 1",
        "row 2"
    ],
    "data": [
        [
            "a",
            "b"
        ],
        [
            "c",
            "d"
        ]
    ]
}
```

Encoding/decoding a Dataframe using `'records'` formatted JSON. Note that index labels are not preserved with this encoding.

```
>>> result = df.to_json(orient="records")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
[
    {
        "col 1": "a",
        "col 2": "b"
    },
    {
        "col 1": "c",
        "col 2": "d"
    }
]
```

Encoding/decoding a Dataframe using `'index'` formatted JSON:

```
>>> result = df.to_json(orient="index")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "row 1": {
        "col 1": "a",
        "col 2": "b"
    },
    "row 2": {
        "col 1": "c",
        "col 2": "d"
    }
}
```

Encoding/decoding a Dataframe using `'columns'` formatted JSON:

```
>>> result = df.to_json(orient="columns")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "col 1": {
        "row 1": "a",
        "row 2": "c"
    },
    "col 2": {
        "row 1": "b",
        "row 2": "d"
    }
}
```

Encoding/decoding a Dataframe using `'values'` formatted JSON:

```
>>> result = df.to_json(orient="values")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
[
    [
        "a",
        "b"
    ],
    [
        "c",
        "d"
    ]
]
```

Encoding with Table Schema:

```
>>> result = df.to_json(orient="table")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "schema": {
        "fields": [
            {
                "name": "index",
                "type": "string"
            },
            {
                "name": "col 1",
                "type": "string"
            },
            {
                "name": "col 2",
                "type": "string"
            }
        ],
        "primaryKey": [
            "index"
        ],
        "pandas_version": "0.20.0"
    },
    "data": [
```

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```
        {
            "index": "row 1",
            "col 1": "a",
            "col 2": "b"
        },
        {
            "index": "row 2",
            "col 1": "c",
            "col 2": "d"
        }
    ]
}
```

pandas.Series.to_latex

Series.**to_latex**(*buf=None*, *columns=None*, *col_space=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *bold_rows=False*, *column_format=None*, *longtable=None*, *escape=None*, *encoding=None*, *decimal='.'*, *multicolumn=None*, *multicolumn_format=None*, *multirow=None*, *caption=None*, *label=None*, *position=None*)

Render object to a LaTeX tabular, longtable, or nested table/tabular.

Requires `\usepackage{booktabs}`. The output can be copy/pasted into a main LaTeX document or read from an external file with `\input{table.tex}`.

Changed in version 1.0.0: Added caption and label arguments.

Changed in version 1.2.0: Added position argument, changed meaning of caption argument.

Parameters

buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

columns [list of label, optional] The subset of columns to write. Writes all columns by default.

col_space [int, optional] The minimum width of each column.

header [bool or list of str, default True] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

na_rep [str, default 'NaN'] Missing data representation.

formatters [list of functions or dict of {str: function}, optional] Formatter functions to apply to columns' elements by position or name. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format [one-parameter function or str, optional, default None] Formatter for floating point numbers. For example `float_format="%.2f"` and `float_format="{:0.2f}".format` will both result in 0.1234 being formatted as 0.12.

sparsify [bool, optional] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row. By default, the value will be read from the config module.

index_names [bool, default True] Prints the names of the indexes.

bold_rows [bool, default False] Make the row labels bold in the output.

column_format [str, optional] The columns format as specified in LaTeX table format e.g. 'rcl' for 3 columns. By default, 'l' will be used for all columns except columns of numbers, which default to 'r'.

longtable [bool, optional] By default, the value will be read from the pandas config module. Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your LaTeX preamble.

escape [bool, optional] By default, the value will be read from the pandas config module. When set to False prevents from escaping latex special characters in column names.

encoding [str, optional] A string representing the encoding to use in the output file, defaults to 'utf-8'.

decimal [str, default '.'] Character recognized as decimal separator, e.g. ',' in Europe.

multicolumn [bool, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

multicolumn_format [str, default 'l'] The alignment for multicolumns, similar to *column_format* The default will be read from the config module.

multirow [bool, default False] Use multirow to enhance MultiIndex rows. Requires adding a usepackage{multirow} to your LaTeX preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

caption [str or tuple, optional] Tuple (full_caption, short_caption), which results in `\caption[short_caption]{full_caption}`; if a single string is passed, no short caption will be set.

New in version 1.0.0.

Changed in version 1.2.0: Optionally allow caption to be a tuple `(full_caption, short_caption)`.

label [str, optional] The LaTeX label to be placed inside `\label{}` in the output. This is used with `\ref{}` in the main `.tex` file.

New in version 1.0.0.

position [str, optional] The LaTeX positional argument for tables, to be placed after `\begin{}` in the output.

New in version 1.2.0.

Returns

str or None If buf is None, returns the result as a string. Otherwise returns None.

See also:

DataFrame.to_string Render a DataFrame to a console-friendly tabular output.

DataFrame.to_html Render a DataFrame as an HTML table.

Examples

```
>>> df = pd.DataFrame(dict(name=['Raphael', 'Donatello'],
...                        mask=['red', 'purple'],
...                        weapon=['sai', 'bo staff']))
>>> print(df.to_latex(index=False))
\begin{tabular}{lll}
 \toprule
       name &    mask &    weapon \\
 \midrule
    Raphael &     red &       sai \\
  Donatello &  purple &  bo staff \\
\bottomrule
\end{tabular}
```

pandas.Series.to_list

Series.**to_list**()

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns

list

See also:

numpy.ndarray.tolist Return the array as an a.ndim-levels deep nested list of Python scalars.

pandas.Series.to_markdown

Series.**to_markdown**(*buf=None*, *mode='wt'*, *index=True*, *storage_options=None*, ***kwargs*)

Print Series in Markdown-friendly format.

New in version 1.0.0.

Parameters

buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

mode [str, optional] Mode in which file is opened, "wt" by default.

index [bool, optional, default True] Add index (row) labels.

New in version 1.1.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

****kwargs** These parameters will be passed to tabulate.

Returns

str Series in Markdown-friendly format.

Notes

Requires the tabulate package.

Examples

```
>>> s = pd.Series(["elk", "pig", "dog", "quetzal"], name="animal")
>>> print(s.to_markdown())
|    | animal   |
|---:|:---------|
|  0 | elk      |
|  1 | pig      |
|  2 | dog      |
|  3 | quetzal  |
```

Output markdown with a tabulate option.

```
>>> print(s.to_markdown(tablefmt="grid"))
+----+----------+
|    | animal   |
+====+==========+
|  0 | elk      |
+----+----------+
|  1 | pig      |
+----+----------+
|  2 | dog      |
+----+----------+
|  3 | quetzal  |
+----+----------+
```

pandas.Series.to_numpy

`Series.`**`to_numpy`**(*dtype=None*, *copy=False*, *na_value=<object object>*, ***kwargs*)

A NumPy ndarray representing the values in this Series or Index.

New in version 0.24.0.

Parameters

dtype [str or numpy.dtype, optional] The dtype to pass to `numpy.asarray()`.

copy [bool, default False] Whether to ensure that the returned value is not a view on another array. Note that `copy=False` does not *ensure* that `to_numpy()` is no-copy. Rather, `copy=True` ensure that a copy is made, even if not strictly necessary.

na_value [Any, optional] The value to use for missing values. The default value depends on *dtype* and the type of the array.

New in version 1.0.0.

****kwargs** Additional keywords passed through to the `to_numpy` method of the underlying array (for extension arrays).

New in version 1.0.0.

Returns

numpy.ndarray

See also:

Series.array Get the actual data stored within.

Index.array Get the actual data stored within.

DataFrame.to_numpy Similar method for DataFrame.

Notes

The returned array will be the same up to equality (values equal in *self* will be equal in the returned array; likewise for values that are not equal). When *self* contains an ExtensionArray, the dtype may be different. For example, for a category-dtype Series, `to_numpy()` will return a NumPy array and the categorical dtype will be lost.

For NumPy dtypes, this will be a reference to the actual data stored in this Series or Index (assuming `copy=False`). Modifying the result in place will modify the data stored in the Series or Index (not that we recommend doing that).

For extension types, `to_numpy()` *may* require copying data and coercing the result to a NumPy type (possibly object), which may be expensive. When you need a no-copy reference to the underlying data, *Series.array* should be used instead.

This table lays out the different dtypes and default return types of `to_numpy()` for various dtypes within pandas.

dtype	array type
category[T]	ndarray[T] (same dtype as input)
period	ndarray[object] (Periods)
interval	ndarray[object] (Intervals)
IntegerNA	ndarray[object]
datetime64[ns]	datetime64[ns]
datetime64[ns, tz]	ndarray[object] (Timestamps)

Examples

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.to_numpy()
array(['a', 'b', 'a'], dtype=object)
```

Specify the *dtype* to control how datetime-aware data is represented. Use `dtype=object` to return an ndarray of pandas *Timestamp* objects, each with the correct `tz`.

```
>>> ser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))
>>> ser.to_numpy(dtype=object)
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or `dtype='datetime64[ns]'` to return an ndarray of native datetime64 values. The values are converted to UTC and the timezone info is dropped.

```
>>> ser.to_numpy(dtype="datetime64[ns]")
...
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00...'],
      dtype='datetime64[ns]')
```

pandas.Series.to_period

Series.**to_period**(*freq=None*, *copy=True*)

Convert Series from DatetimeIndex to PeriodIndex.

Parameters

freq [str, default None] Frequency associated with the PeriodIndex.

copy [bool, default True] Whether or not to return a copy.

Returns

Series Series with index converted to PeriodIndex.

pandas.Series.to_pickle

Series.**to_pickle**(*path*, *compression='infer'*, *protocol=5*, *storage_options=None*)

Pickle (serialize) object to file.

Parameters

path [str] File path where the pickled object will be stored.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'] A string representing the compression to use in the output file. By default, infers from the file extension in specified path. Compression mode may be any of the following possible values: {'infer', 'gzip', 'bz2', 'zip', 'xz', None}. If compression mode is 'infer' and path_or_buf is path-like, then detect compression mode from the following extensions: '.gz', '.bz2', '.zip' or '.xz'. (otherwise no compression). If dict given and mode is 'zip' or inferred as 'zip', other entries passed as additional compression options.

protocol [int] Int which indicates which protocol should be used by the pickler, default HIGHEST_PROTOCOL (see [1] paragraph 12.1.2). The possible values are 0, 1, 2, 3, 4, 5. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST_PROTOCOL.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

See also:

read_pickle Load pickled pandas object (or any object) from file.

DataFrame.to_hdf Write DataFrame to an HDF5 file.

DataFrame.to_sql Write DataFrame to a SQL database.

DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Examples

```
>>> original_df = pd.DataFrame({"foo": range(5), "bar": range(5, 10)})
>>> original_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
>>> original_df.to_pickle("./dummy.pkl")
```

```
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
```

```
>>> import os
>>> os.remove("./dummy.pkl")
```

pandas.Series.to_sql

Series.**to_sql**(*name*, *con*, *schema=None*, *if_exists='fail'*, *index=True*, *index_label=None*, *chunksize=None*, *dtype=None*, *method=None*)

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [1] are supported. Tables can be newly created, appended to, or overwritten.

Parameters

name [str] Name of SQL table.

con [sqlalchemy.engine.(Engine or Connection) or sqlite3.Connection] Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable See here.

schema [str, optional] Specify the schema (if database flavor supports this). If None, use default schema.

if_exists [{'fail', 'replace', 'append'}, default 'fail'] How to behave if the table already exists.

- fail: Raise a ValueError.
- replace: Drop the table before inserting new values.

- append: Insert new values to the existing table.

index [bool, default True] Write DataFrame index as a column. Uses *index_label* as the column name in the table.

index_label [str or sequence, default None] Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize [int, optional] Specify the number of rows in each batch to be written at a time. By default, all rows will be written at once.

dtype [dict or scalar, optional] Specifying the datatype for columns. If a dictionary is used, the keys should be the column names and the values should be the SQLAlchemy types or strings for the sqlite3 legacy mode. If a scalar is provided, it will be applied to all columns.

method [{None, 'multi', callable}, optional] Controls the SQL insertion clause used:

- None : Uses standard SQL `INSERT` clause (one per row).
- 'multi': Pass multiple values in a single `INSERT` clause.
- callable with signature `(pd_table, conn, keys, data_iter)`.

Details and a sample callable implementation can be found in the section *insert method*.

New in version 0.24.0.

Raises

ValueError When the table already exists and *if_exists* is 'fail' (the default).

See also:

read_sql Read a DataFrame from a table.

Notes

Timezone aware datetime columns will be written as `Timestamp with timezone` type with SQLAlchemy if supported by the database. Otherwise, the datetimes will be stored as timezone unaware timestamps local to the original timezone.

New in version 0.24.0.

References

[1], [2]

Examples

Create an in-memory SQLite database.

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})
>>> df
     name
0  User 1
1  User 2
2  User 3
```

```
>>> df.to_sql('users', con=engine)
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]
```

An *sqlalchemy.engine.Connection* can also be passed to *con*:

```
>>> with engine.begin() as connection:
...     df1 = pd.DataFrame({'name' : ['User 4', 'User 5']})
...     df1.to_sql('users', con=connection, if_exists='append')
```

This is allowed to support operations that require that the same DBAPI connection is used for the entire operation.

```
>>> df2 = pd.DataFrame({'name' : ['User 6', 'User 7']})
>>> df2.to_sql('users', con=engine, if_exists='append')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3'),
 (0, 'User 4'), (1, 'User 5'), (0, 'User 6'),
 (1, 'User 7')]
```

Overwrite the table with just `df2`.

```
>>> df2.to_sql('users', con=engine, if_exists='replace',
...            index_label='id')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 6'), (1, 'User 7')]
```

Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```
>>> df = pd.DataFrame({"A": [1, None, 2]})
>>> df
     A
0  1.0
1  NaN
2  2.0
```

```
>>> from sqlalchemy.types import Integer
>>> df.to_sql('integers', con=engine, index=False,
...           dtype={"A": Integer()})
```

```
>>> engine.execute("SELECT * FROM integers").fetchall()
[(1,), (None,), (2,)]
```

pandas.Series.to_string

Series.**to_string**(*buf=None*, *na_rep='NaN'*, *float_format=None*, *header=True*, *index=True*, *length=False*, *dtype=False*, *name=False*, *max_rows=None*, *min_rows=None*)

Render a string representation of the Series.

Parameters

buf [StringIO-like, optional] Buffer to write to.

na_rep [str, optional] String representation of NaN to use, default 'NaN'.

float_format [one-parameter function, optional] Formatter function to apply to columns' elements if they are floats, default None.

header [bool, default True] Add the Series header (index name).

index [bool, optional] Add index (row) labels, default True.

length [bool, default False] Add the Series length.

dtype [bool, default False] Add the Series dtype.

name [bool, default False] Add the Series name if not None.

max_rows [int, optional] Maximum number of rows to show before truncating. If None, show all.

min_rows [int, optional] The number of rows to display in a truncated repr (when number of rows is above *max_rows*).

Returns

str or None String representation of Series if `buf=None`, otherwise None.

pandas.Series.to_timestamp

Series.**to_timestamp**(*freq=None*, *how='start'*, *copy=True*)

Cast to DatetimeIndex of Timestamps, at *beginning* of period.

Parameters

freq [str, default frequency of PeriodIndex] Desired frequency.

how [{'s', 'e', 'start', 'end'}] Convention for converting period to timestamp; start of period vs. end.

copy [bool, default True] Whether or not to return a copy.

Returns

Series with DatetimeIndex

pandas.Series.to_xarray

Series.**to_xarray**()

Return an xarray object from the pandas object.

Returns

xarray.DataArray or xarray.Dataset Data in the pandas structure converted to Dataset if the object is a DataFrame, or a DataArray if the object is a Series.

See also:

DataFrame.to_hdf Write DataFrame to an HDF5 file.

DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Notes

See the xarray docs

Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0, 2),
...                    ('parrot', 'bird', 24.0, 2),
...                    ('lion', 'mammal', 80.5, 4),
...                    ('monkey', 'mammal', np.nan, 4)],
...                   columns=['name', 'class', 'max_speed',
...                            'num_legs'])
>>> df
     name   class  max_speed  num_legs
0  falcon    bird      389.0         2
1  parrot    bird       24.0         2
2    lion  mammal       80.5         4
3  monkey  mammal        NaN         4
```

```
>>> df.to_xarray()
<xarray.Dataset>
Dimensions:    (index: 4)
Coordinates:
  * index      (index) int64 0 1 2 3
Data variables:
    name       (index) object 'falcon' 'parrot' 'lion' 'monkey'
    class      (index) object 'bird' 'bird' 'mammal' 'mammal'
    max_speed  (index) float64 389.0 24.0 80.5 nan
    num_legs   (index) int64 2 2 4 4
```

```
>>> df['max_speed'].to_xarray()
<xarray.DataArray 'max_speed' (index: 4)>
array([389. ,  24. ,  80.5,   nan])
Coordinates:
  * index    (index) int64 0 1 2 3
```

```
>>> dates = pd.to_datetime(['2018-01-01', '2018-01-01',
...                         '2018-01-02', '2018-01-02'])
>>> df_multiindex = pd.DataFrame({'date': dates,
```

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```
...                                 'animal': ['falcon', 'parrot',
...                                           'falcon', 'parrot'],
...                                 'speed': [350, 18, 361, 15]})
>>> df_multiindex = df_multiindex.set_index(['date', 'animal'])
```

```
>>> df_multiindex
                   speed
date       animal
2018-01-01 falcon    350
           parrot     18
2018-01-02 falcon    361
           parrot     15
```

```
>>> df_multiindex.to_xarray()
<xarray.Dataset>
Dimensions:  (animal: 2, date: 2)
Coordinates:
  * date     (date) datetime64[ns] 2018-01-01 2018-01-02
  * animal   (animal) object 'falcon' 'parrot'
Data variables:
    speed    (date, animal) int64 350 18 361 15
```

pandas.Series.tolist

Series.**tolist**()

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns

list

See also:

numpy.ndarray.tolist Return the array as an a.ndim-levels deep nested list of Python scalars.

pandas.Series.transform

Series.**transform**(*func*, *axis=0*, **args*, ***kwargs*)

Call `func` on self producing a Series with transformed values.

Produced Series will have same axis length as self.

Parameters

func [function, str, list-like or dict-like] Function to use for transforming the data. If a function, must either work when passed a Series or when passed to Series.apply. If func is both list-like and dict-like, dict-like behavior takes precedence.

Accepted combinations are:

- function
- string function name

- list-like of functions and/or function names, e.g. `[np.exp, 'sqrt']`
- dict-like of axis labels -> functions, function names or list-like of such.

axis [{0 or 'index'}] Parameter needed for compatibility with DataFrame.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

Series A Series that must have the same length as self.

Raises

ValueError [If the returned Series has a different length than self.]

See also:

Series.agg Only perform aggregating type operations.

Series.apply Invoke function on a Series.

Examples

```
>>> df = pd.DataFrame({'A': range(3), 'B': range(1, 4)})
>>> df
   A  B
0  0  1
1  1  2
2  2  3
>>> df.transform(lambda x: x + 1)
   A  B
0  1  2
1  2  3
2  3  4
```

Even though the resulting Series must have the same length as the input Series, it is possible to provide several input functions:

```
>>> s = pd.Series(range(3))
>>> s
0    0
1    1
2    2
dtype: int64
>>> s.transform([np.sqrt, np.exp])
       sqrt        exp
0  0.000000   1.000000
1  1.000000   2.718282
2  1.414214   7.389056
```

You can call transform on a GroupBy object:

```
>>> df = pd.DataFrame({
...     "Date": [
...         "2015-05-08", "2015-05-07", "2015-05-06", "2015-05-05",
...         "2015-05-08", "2015-05-07", "2015-05-06", "2015-05-05"],
...     "Data": [5, 8, 6, 1, 50, 100, 60, 120],
```

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```
... })
>>> df
         Date  Data
0  2015-05-08     5
1  2015-05-07     8
2  2015-05-06     6
3  2015-05-05     1
4  2015-05-08    50
5  2015-05-07   100
6  2015-05-06    60
7  2015-05-05   120
>>> df.groupby('Date')['Data'].transform('sum')
0     55
1    108
2     66
3    121
4     55
5    108
6     66
7    121
Name: Data, dtype: int64
```

```
>>> df = pd.DataFrame({
...     "c": [1, 1, 1, 2, 2, 2, 2],
...     "type": ["m", "n", "o", "m", "m", "n", "n"]
... })
>>> df
   c type
0  1    m
1  1    n
2  1    o
3  2    m
4  2    m
5  2    n
6  2    n
>>> df['size'] = df.groupby('c')['type'].transform(len)
>>> df
   c type size
0  1    m    3
1  1    n    3
2  1    o    3
3  2    m    4
4  2    m    4
5  2    n    4
6  2    n    4
```

pandas.Series.transpose

Series.**transpose**(**args*, ***kwargs*)

Return the transpose, which is by definition self.

Returns

%(klass)s

pandas.Series.truediv

Series.**truediv**(*other*, *level=None*, *fill_value=None*, *axis=0*)

Return Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rtruediv Reverse of the Floating division operator, see Python documentation for more details.

Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
```

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```
c    inf
d    0.0
e    NaN
dtype: float64
```

pandas.Series.truncate

Series.**truncate**(*before=None*, *after=None*, *axis=None*, *copy=True*)

Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

Parameters

before [date, str, int] Truncate all rows before this index value.

after [date, str, int] Truncate all rows after this index value.

axis [{0 or 'index', 1 or 'columns'}, optional] Axis to truncate. Truncates the index (rows) by default.

copy [bool, default is True,] Return a copy of the truncated section.

Returns

type of caller The truncated Series or DataFrame.

See also:

DataFrame.loc Select a subset of a DataFrame by label.

DataFrame.iloc Select a subset of a DataFrame by position.

Notes

If the index being truncated contains only datetime values, *before* and *after* may be specified as strings instead of Timestamps.

Examples

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
...                    'B': ['f', 'g', 'h', 'i', 'j'],
...                    'C': ['k', 'l', 'm', 'n', 'o']},
...                   index=[1, 2, 3, 4, 5])
>>> df
   A  B  C
1  a  f  k
2  b  g  l
3  c  h  m
4  d  i  n
5  e  j  o
```

```
>>> df.truncate(before=2, after=4)
   A  B  C
2  b  g  l
3  c  h  m
4  d  i  n
```

The columns of a DataFrame can be truncated.

```
>>> df.truncate(before="A", after="B", axis="columns")
   A  B
1  a  f
2  b  g
3  c  h
4  d  i
5  e  j
```

For Series, only rows can be truncated.

```
>>> df['A'].truncate(before=2, after=4)
2    b
3    c
4    d
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={'A': 1})
>>> df.tail()
                     A
2016-01-31 23:59:56  1
2016-01-31 23:59:57  1
2016-01-31 23:59:58  1
2016-01-31 23:59:59  1
2016-02-01 00:00:00  1
```

```
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
...             after=pd.Timestamp('2016-01-10')).tail()
                     A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Because the index is a DatetimeIndex containing only dates, we can specify *before* and *after* as strings. They will be coerced to Timestamps before truncation.

```
>>> df.truncate('2016-01-05', '2016-01-10').tail()
                     A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
                     A
2016-01-10 23:59:55  1
2016-01-10 23:59:56  1
2016-01-10 23:59:57  1
2016-01-10 23:59:58  1
2016-01-10 23:59:59  1
```

pandas.Series.tshift

Series.**tshift**(*periods=1*, *freq=None*, *axis=0*)

Shift the time index, using the index's frequency if available.

Deprecated since version 1.1.0: Use *shift* instead.

Parameters

periods [int] Number of periods to move, can be positive or negative.

freq [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. 'EOM').

axis [{0 or 'index', 1 or 'columns', None}, default 0] Corresponds to the axis that contains the Index.

Returns

shifted [Series/DataFrame]

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

pandas.Series.tz_convert

Series.**tz_convert**(*tz*, *axis=0*, *level=None*, *copy=True*)

Convert tz-aware axis to target time zone.

Parameters

tz [str or tzinfo object]

axis [the axis to convert]

level [int, str, default None] If axis is a MultiIndex, convert a specific level. Otherwise must be None.

copy [bool, default True] Also make a copy of the underlying data.

Returns

{klass} Object with time zone converted axis.

Raises

TypeError If the axis is tz-naive.

pandas.Series.tz_localize

Series.**tz_localize**(*tz*, *axis=0*, *level=None*, *copy=True*, *ambiguous='raise'*, *nonexistent='raise'*)

Localize tz-naive index of a Series or DataFrame to target time zone.

This operation localizes the Index. To localize the values in a timezone-naive Series, use *Series.dt.tz_localize()*.

Parameters

tz [str or tzinfo]

axis [the axis to localize]

level [int, str, default None] If axis ia a MultiIndex, localize a specific level. Otherwise must be None.

copy [bool, default True] Also make a copy of the underlying data.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

nonexistent [str, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST. Valid values are:

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

Series or DataFrame Same type as the input.

Raises

TypeError If the TimeSeries is tz-aware and tz is not None.

Examples

Localize local times:

```
>>> s = pd.Series([1],
...               index=pd.DatetimeIndex(['2018-09-15 01:30:00']))
>>> s.tz_localize('CET')
2018-09-15 01:30:00+02:00    1
dtype: int64
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.Series(range(7),
...               index=pd.DatetimeIndex(['2018-10-28 01:30:00',
...                                       '2018-10-28 02:00:00',
...                                       '2018-10-28 02:30:00',
...                                       '2018-10-28 02:00:00',
...                                       '2018-10-28 02:30:00',
...                                       '2018-10-28 03:00:00',
...                                       '2018-10-28 03:30:00']))
>>> s.tz_localize('CET', ambiguous='infer')
2018-10-28 01:30:00+02:00    0
2018-10-28 02:00:00+02:00    1
2018-10-28 02:30:00+02:00    2
2018-10-28 02:00:00+01:00    3
2018-10-28 02:30:00+01:00    4
2018-10-28 03:00:00+01:00    5
2018-10-28 03:30:00+01:00    6
dtype: int64
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```
>>> s = pd.Series(range(3),
...               index=pd.DatetimeIndex(['2018-10-28 01:20:00',
...                                       '2018-10-28 02:36:00',
...                                       '2018-10-28 03:46:00']))
>>> s.tz_localize('CET', ambiguous=np.array([True, True, False]))
2018-10-28 01:20:00+02:00    0
2018-10-28 02:36:00+02:00    1
2018-10-28 03:46:00+01:00    2
dtype: int64
```

If the DST transition causes nonexistent times, you can shift these dates forward or backward with a timedelta object or *'shift_forward'* or *'shift_backward'*.

```
>>> s = pd.Series(range(2),
...               index=pd.DatetimeIndex(['2015-03-29 02:30:00',
...                                       '2015-03-29 03:30:00']))
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
2015-03-29 03:00:00+02:00    0
2015-03-29 03:30:00+02:00    1
dtype: int64
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
2015-03-29 01:59:59.999999999+01:00    0
2015-03-29 03:30:00+02:00              1
dtype: int64
>>> s.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
```

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```
2015-03-29 03:30:00+02:00    0
2015-03-29 03:30:00+02:00    1
dtype: int64
```

pandas.Series.unique

Series.**unique**()

Return unique values of Series object.

Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

Returns

ndarray or ExtensionArray The unique values returned as a NumPy array. See Notes.

See also:

unique Top-level unique method for any 1-d array-like object.

Index.unique Return Index with unique values from an Index object.

Notes

Returns the unique values as a NumPy array. In case of an extension-array backed Series, a new *ExtensionArray* of that type with just the unique values is returned. This includes

- Categorical
- Period
- Datetime with Timezone
- Interval
- Sparse
- IntegerNA

See Examples section.

Examples

```
>>> pd.Series([2, 1, 3, 3], name='A').unique()
array([2, 1, 3])
```

```
>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern')
...             for _ in range(3)]).unique()
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]
```

An unordered Categorical will return categories in the order of appearance.

```
>>> pd.Series(pd.Categorical(list('baabc'))).unique()
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```

An ordered Categorical preserves the category ordering.

```
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'),
...                          ordered=True)).unique()
['b', 'a', 'c']
Categories (3, object): ['a' < 'b' < 'c']
```

pandas.Series.unstack

Series.**unstack**(*level=-1*, *fill_value=None*)

Unstack, also known as pivot, Series with MultiIndex to produce DataFrame.

Parameters

level [int, str, or list of these, default last level] Level(s) to unstack, can pass level name.

fill_value [scalar value, default None] Value to use when replacing NaN values.

Returns

DataFrame Unstacked Series.

Examples

```
>>> s = pd.Series([1, 2, 3, 4],
...               index=pd.MultiIndex.from_product([['one', 'two'],
...                                                 ['a', 'b']]))
>>> s
one  a    1
     b    2
two  a    3
     b    4
dtype: int64
```

```
>>> s.unstack(level=-1)
     a  b
one  1  2
two  3  4
```

```
>>> s.unstack(level=0)
   one  two
a    1    3
b    2    4
```

pandas.Series.update

Series.**update**(*other*)

Modify Series in place using values from passed Series.

Uses non-NA values from passed Series to make updates. Aligns on index.

Parameters

other [Series, or object coercible into Series]

Examples

```
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, 5, 6]))
>>> s
0    4
1    5
2    6
dtype: int64
```

```
>>> s = pd.Series(['a', 'b', 'c'])
>>> s.update(pd.Series(['d', 'e'], index=[0, 2]))
>>> s
0    d
1    b
2    e
dtype: object
```

```
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, 5, 6, 7, 8]))
>>> s
0    4
1    5
2    6
dtype: int64
```

If `other` contains NaNs the corresponding values are not updated in the original Series.

```
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, np.nan, 6]))
>>> s
0    4
1    2
2    6
dtype: int64
```

`other` can also be a non-Series object type that is coercible into a Series

```
>>> s = pd.Series([1, 2, 3])
>>> s.update([4, np.nan, 6])
>>> s
0    4
1    2
2    6
dtype: int64
```

```
>>> s = pd.Series([1, 2, 3])
>>> s.update({1: 9})
>>> s
0    1
1    9
2    3
dtype: int64
```

pandas.Series.value_counts

Series.**value_counts**(*normalize=False*, *sort=True*, *ascending=False*, *bins=None*, *dropna=True*)

Return a Series containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters

normalize [bool, default False] If True then the object returned will contain the relative frequencies of the unique values.

sort [bool, default True] Sort by frequencies.

ascending [bool, default False] Sort in ascending order.

bins [int, optional] Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data.

dropna [bool, default True] Don't include counts of NaN.

Returns

Series

See also:

Series.count Number of non-NA elements in a Series.

DataFrame.count Number of non-NA elements in a DataFrame.

DataFrame.value_counts Equivalent method on DataFrames.

Examples

```
>>> index = pd.Index([3, 1, 2, 3, 4, np.nan])
>>> index.value_counts()
3.0    2
2.0    1
4.0    1
1.0    1
dtype: int64
```

With *normalize* set to *True*, returns the relative frequency by dividing all values by the sum of values.

```
>>> s = pd.Series([3, 1, 2, 3, 4, np.nan])
>>> s.value_counts(normalize=True)
3.0    0.4
```

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```
2.0    0.2
4.0    0.2
1.0    0.2
dtype: float64
```

bins

Bins can be useful for going from a continuous variable to a categorical variable; instead of counting unique apparitions of values, divide the index in the specified number of half-open bins.

```
>>> s.value_counts(bins=3)
(0.996, 2.0]    2
(2.0, 3.0]      2
(3.0, 4.0]      1
dtype: int64
```

dropna

With *dropna* set to *False* we can also see NaN index values.

```
>>> s.value_counts(dropna=False)
3.0    2
2.0    1
NaN    1
4.0    1
1.0    1
dtype: int64
```

pandas.Series.var

Series.**var**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis [{index (0)}]

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

scalar or Series (if level specified)

Notes

To have the same behaviour as *numpy.std*, use *ddof=0* (instead of the default *ddof=1*)

pandas.Series.view

Series.**view**(*dtype=None*)

Create a new view of the Series.

This function will return a new Series with a view of the same underlying values in memory, optionally reinterpreted with a new data type. The new data type must preserve the same size in bytes as to not cause index misalignment.

Parameters

dtype [data type] Data type object or one of their string representations.

Returns

Series A new Series object as a view of the same data in memory.

See also:

numpy.ndarray.view Equivalent numpy function to create a new view of the same data in memory.

Notes

Series are instantiated with `dtype=float64` by default. While `numpy.ndarray.view()` will return a view with the same data type as the original array, `Series.view()` (without specified dtype) will try using `float64` and may fail if the original data type size in bytes is not the same.

Examples

```
>>> s = pd.Series([-2, -1, 0, 1, 2], dtype='int8')
>>> s
0   -2
1   -1
2    0
3    1
4    2
dtype: int8
```

The 8 bit signed integer representation of *-1* is *0b11111111*, but the same bytes represent 255 if read as an 8 bit unsigned integer:

```
>>> us = s.view('uint8')
>>> us
0    254
1    255
2      0
3      1
4      2
dtype: uint8
```

The views share the same underlying values:

```
>>> us[0] = 128
>>> s
0   -128
1     -1
2      0
3      1
4      2
dtype: int8
```

pandas.Series.where

Series.**where**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *errors='raise'*, *try_cast=False*)

Replace values where the condition is False.

Parameters

cond [bool Series/DataFrame, array-like, or callable] Where *cond* is True, keep the original value. Where False, replace with corresponding value from *other*. If *cond* is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

other [scalar, Series/DataFrame, or callable] Entries where *cond* is False are replaced with corresponding value from *other*. If other is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

inplace [bool, default False] Whether to perform the operation in place on the data.

axis [int, default None] Alignment axis if needed.

level [int, default None] Alignment level if needed.

errors [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won't affect the results and will always coerce to a suitable dtype.

- 'raise' : allow exceptions to be raised.
- 'ignore' : suppress exceptions. On error return original object.

try_cast [bool, default False] Try to cast the result back to the input type (if possible).

Returns

Same type as caller or None if `inplace=True`.

See also:

DataFrame.mask() Return an object of same shape as self.

Notes

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if `cond` is `True` the element is used; otherwise the corresponding element from the DataFrame `other` is used.

The signature for *`DataFrame.where()`* differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the `where` documentation in *indexing*.

Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0
dtype: float64
>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0    10
1    10
2    2
3    3
4    4
dtype: int64
>>> s.mask(s > 1, 10)
0     0
1     1
2    10
3    10
4    10
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
4  8  9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0  0 -1
```

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```
1 -2  3
2 -4 -5
3  6 -7
4 -8  9
>>> df.where(m, -df) == np.where(m, df, -df)
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

pandas.Series.xs

Series.**xs**(*key*, *axis=0*, *level=None*, *drop_level=True*)

Return cross-section from the Series/DataFrame.

This method takes a *key* argument to select data at a particular level of a MultiIndex.

Parameters

key [label or tuple of label] Label contained in the index, or partially in a MultiIndex.

axis [{0 or 'index', 1 or 'columns'}, default 0] Axis to retrieve cross-section on.

level [object, defaults to first n levels (n=1 or len(key))] In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

drop_level [bool, default True] If False, returns object with same levels as self.

Returns

Series or DataFrame Cross-section from the original Series or DataFrame corresponding to the selected index levels.

See also:

DataFrame.loc Access a group of rows and columns by label(s) or a boolean array.

DataFrame.iloc Purely integer-location based indexing for selection by position.

Notes

xs can not be used to set values.

MultiIndex Slicers is a generic way to get/set values on any level or levels. It is a superset of *xs* functionality, see *MultiIndex Slicers*.

Examples

```
>>> d = {'num_legs': [4, 4, 2, 2],
...      'num_wings': [0, 0, 2, 2],
...      'class': ['mammal', 'mammal', 'mammal', 'bird'],
...      'animal': ['cat', 'dog', 'bat', 'penguin'],
...      'locomotion': ['walks', 'walks', 'flies', 'walks']}
>>> df = pd.DataFrame(data=d)
>>> df = df.set_index(['class', 'animal', 'locomotion'])
>>> df
                           num_legs  num_wings
class  animal  locomotion
mammal cat     walks              4          0
       dog     walks              4          0
       bat     flies              2          2
bird   penguin walks              2          2
```

Get values at specified index

```
>>> df.xs('mammal')
                    num_legs  num_wings
animal locomotion
cat    walks              4          0
dog    walks              4          0
bat    flies              2          2
```

Get values at several indexes

```
>>> df.xs(('mammal', 'dog'))
            num_legs  num_wings
locomotion
walks              4          0
```

Get values at specified index and level

```
>>> df.xs('cat', level=1)
                    num_legs  num_wings
class  locomotion
mammal walks              4          0
```

Get values at several indexes and levels

```
>>> df.xs(('bird', 'walks'),
...       level=[0, 'locomotion'])
         num_legs  num_wings
animal
penguin         2          2
```

Get values at specified column and axis

```
>>> df.xs('num_wings', axis=1)
class   animal   locomotion
mammal  cat      walks         0
        dog      walks         0
        bat      flies         2
bird    penguin  walks         2
Name: num_wings, dtype: int64
```

3.3.2 Attributes

Axes

Series.index	The index (axis labels) of the Series.
Series.array	The ExtensionArray of the data backing this Series or Index.
Series.values	Return Series as ndarray or ndarray-like depending on the dtype.
Series.dtype	Return the dtype object of the underlying data.
Series.shape	Return a tuple of the shape of the underlying data.
Series.nbytes	Return the number of bytes in the underlying data.
Series.ndim	Number of dimensions of the underlying data, by definition 1.
Series.size	Return the number of elements in the underlying data.
Series.T	Return the transpose, which is by definition self.
Series.memory_usage([index, deep])	Return the memory usage of the Series.
Series.hasnans	Return if I have any nans; enables various perf speedups.
Series.empty	Indicator whether DataFrame is empty.
Series.dtypes	Return the dtype object of the underlying data.
Series.name	Return the name of the Series.
Series.flags	Get the properties associated with this pandas object.
Series.set_flags(*[, copy, ...])	Return a new object with updated flags.

pandas.Series.empty

property Series.**empty**

Indicator whether DataFrame is empty.

True if DataFrame is entirely empty (no items), meaning any of the axes are of length 0.

Returns

bool If DataFrame is empty, return True, if not return False.

See also:

Series.dropna Return series without null values.

DataFrame.dropna Return DataFrame with labels on given axis omitted where (all or any) data are missing.

Notes

If DataFrame contains only NaNs, it is still not considered empty. See the example below.

Examples

An example of an actual empty DataFrame. Notice the index is empty:

```
>>> df_empty = pd.DataFrame({'A' : []})
>>> df_empty
Empty DataFrame
Columns: [A]
Index: []
>>> df_empty.empty
True
```

If we only have NaNs in our DataFrame, it is not considered empty! We will need to drop the NaNs to make the DataFrame empty:

```
>>> df = pd.DataFrame({'A' : [np.nan]})
>>> df
    A
0 NaN
>>> df.empty
False
>>> df.dropna().empty
True
```

3.3.3 Conversion

Series.astype(dtype[, copy, errors])	Cast a pandas object to a specified dtype `dtype`.
Series.convert_dtypes([infer_objects, ...])	Convert columns to best possible dtypes using dtypes supporting `pd.NA`.
Series.infer_objects()	Attempt to infer better dtypes for object columns.
Series.copy([deep])	Make a copy of this object's indices and data.
Series.bool()	Return the bool of a single element Series or DataFrame.
Series.to_numpy([dtype, copy, na_value])	A NumPy ndarray representing the values in this Series or Index.
Series.to_period([freq, copy])	Convert Series from DatetimeIndex to PeriodIndex.
Series.to_timestamp([freq, how, copy])	Cast to DatetimeIndex of Timestamps, at *beginning* of period.
Series.to_list()	Return a list of the values.
Series.__array__([dtype])	Return the values as a NumPy array.

pandas.Series.__array__

Series.**__array__**(*dtype=None*)

Return the values as a NumPy array.

Users should not call this directly. Rather, it is invoked by `numpy.array()` and `numpy.asarray()`.

Parameters

dtype [str or numpy.dtype, optional] The dtype to use for the resulting NumPy array. By default, the dtype is inferred from the data.

Returns

numpy.ndarray The values in the series converted to a `numpy.ndarray` with the specified *dtype*.

See also:

array Create a new array from data.
Series.array Zero-copy view to the array backing the Series.
Series.to_numpy Series method for similar behavior.

Examples

```
>>> ser = pd.Series([1, 2, 3])
>>> np.asarray(ser)
array([1, 2, 3])
```

For timezone-aware data, the timezones may be retained with `dtype='object'`

```
>>> tzser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))
>>> np.asarray(tzser, dtype="object")
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or the values may be localized to UTC and the tzinfo discarded with `dtype='datetime64[ns]'`

```
>>> np.asarray(tzser, dtype="datetime64[ns]")
array(['1999-12-31T23:00:00.000000000', ...],
      dtype='datetime64[ns]')
```

3.3.4 Indexing, iteration

Series.get(key[, default])	Get item from object for given key (ex: DataFrame column).
Series.at	Access a single value for a row/column label pair.
Series.iat	Access a single value for a row/column pair by integer position.
Series.loc	Access a group of rows and columns by label(s) or a boolean array.
Series.iloc	Purely integer-location based indexing for selection by position.
Series.__iter__()	Return an iterator of the values.

continues on next page

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Series.items()	Lazily iterate over (index, value) tuples.
Series.iteritems()	Lazily iterate over (index, value) tuples.
Series.keys()	Return alias for index.
Series.pop(item)	Return item and drops from series.
Series.item()	Return the first element of the underlying data as a Python scalar.
Series.xs(key[, axis, level, drop_level])	Return cross-section from the Series/DataFrame.

pandas.Series.__iter__

Series.__iter__()

Return an iterator of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns

iterator

For more information on `.at`, `.iat`, `.loc`, and `.iloc`, see the *indexing documentation*.

3.3.5 Binary operator functions

Series.add(other[, level, fill_value, axis])	Return Addition of series and other, element-wise (binary operator *add*).
Series.sub(other[, level, fill_value, axis])	Return Subtraction of series and other, element-wise (binary operator *sub*).
Series.mul(other[, level, fill_value, axis])	Return Multiplication of series and other, element-wise (binary operator *mul*).
Series.div(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *truediv*).
Series.truediv(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *truediv*).
Series.floordiv(other[, level, fill_value, axis])	Return Integer division of series and other, element-wise (binary operator *floordiv*).
Series.mod(other[, level, fill_value, axis])	Return Modulo of series and other, element-wise (binary operator *mod*).
Series.pow(other[, level, fill_value, axis])	Return Exponential power of series and other, element-wise (binary operator *pow*).
Series.radd(other[, level, fill_value, axis])	Return Addition of series and other, element-wise (binary operator *radd*).
Series.rsub(other[, level, fill_value, axis])	Return Subtraction of series and other, element-wise (binary operator *rsub*).
Series.rmul(other[, level, fill_value, axis])	Return Multiplication of series and other, element-wise (binary operator *rmul*).
Series.rdiv(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *rtruediv*).
Series.rtruediv(other[, level, fill_value, axis])	Return Floating division of series and other, element-wise (binary operator *rtruediv*).

continues on next page

Table 33 – continued from previous page

Series.rfloordiv(other[, level, fill_value, ...])	Return Integer division of series and other, element-wise (binary operator *rfloordiv*).
Series.rmod(other[, level, fill_value, axis])	Return Modulo of series and other, element-wise (binary operator *rmod*).
Series.rpow(other[, level, fill_value, axis])	Return Exponential power of series and other, element-wise (binary operator *rpow*).
Series.combine(other, func[, fill_value])	Combine the Series with a Series or scalar according to *func*.
Series.combine_first(other)	Combine Series values, choosing the calling Series's values first.
Series.round([decimals])	Round each value in a Series to the given number of decimals.
Series.lt(other[, level, fill_value, axis])	Return Less than of series and other, element-wise (binary operator *lt*).
Series.gt(other[, level, fill_value, axis])	Return Greater than of series and other, element-wise (binary operator *gt*).
Series.le(other[, level, fill_value, axis])	Return Less than or equal to of series and other, element-wise (binary operator *le*).
Series.ge(other[, level, fill_value, axis])	Return Greater than or equal to of series and other, element-wise (binary operator *ge*).
Series.ne(other[, level, fill_value, axis])	Return Not equal to of series and other, element-wise (binary operator *ne*).
Series.eq(other[, level, fill_value, axis])	Return Equal to of series and other, element-wise (binary operator *eq*).
Series.product([axis, skipna, level, ...])	Return the product of the values over the requested axis.
Series.dot(other)	Compute the dot product between the Series and the columns of other.

3.3.6 Function application, GroupBy & window

Series.apply(func[, convert_dtype, args])	Invoke function on values of Series.
Series.agg([func, axis])	Aggregate using one or more operations over the specified axis.
Series.aggregate([func, axis])	Aggregate using one or more operations over the specified axis.
Series.transform(func[, axis])	Call `func` on self producing a Series with transformed values.
Series.map(arg[, na_action])	Map values of Series according to input correspondence.
Series.groupby([by, axis, level, as_index, ...])	Group Series using a mapper or by a Series of columns.
Series.rolling(window[, min_periods, ...])	Provide rolling window calculations.
Series.expanding([min_periods, center, axis])	Provide expanding transformations.
Series.ewm([com, span, halflife, alpha, ...])	Provide exponential weighted (EW) functions.
Series.pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs).

3.3.7 Computations / descriptive stats

Series.abs()	Return a Series/DataFrame with absolute numeric value of each element.
Series.all([axis, bool_only, skipna, level])	Return whether all elements are True, potentially over an axis.
Series.any([axis, bool_only, skipna, level])	Return whether any element is True, potentially over an axis.
Series.autocorr([lag])	Compute the lag-N autocorrelation.
Series.between(left, right[, inclusive])	Return boolean Series equivalent to left <= series <= right.
Series.clip([lower, upper, axis, inplace])	Trim values at input threshold(s).
Series.corr(other[, method, min_periods])	Compute correlation with *other* Series, excluding missing values.
Series.count([level])	Return number of non-NA/null observations in the Series.
Series.cov(other[, min_periods, ddof])	Compute covariance with Series, excluding missing values.
Series.cummax([axis, skipna])	Return cumulative maximum over a DataFrame or Series axis.
Series.cummin([axis, skipna])	Return cumulative minimum over a DataFrame or Series axis.
Series.cumprod([axis, skipna])	Return cumulative product over a DataFrame or Series axis.
Series.cumsum([axis, skipna])	Return cumulative sum over a DataFrame or Series axis.
Series.describe([percentiles, include, ...])	Generate descriptive statistics.
Series.diff([periods])	First discrete difference of element.
Series.factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable.
Series.kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis.
Series.mad([axis, skipna, level])	Return the mean absolute deviation of the values over the requested axis.
Series.max([axis, skipna, level, numeric_only])	Return the maximum of the values over the requested axis.
Series.mean([axis, skipna, level, numeric_only])	Return the mean of the values over the requested axis.
Series.median([axis, skipna, level, ...])	Return the median of the values over the requested axis.
Series.min([axis, skipna, level, numeric_only])	Return the minimum of the values over the requested axis.
Series.mode([dropna])	Return the mode(s) of the Series.
Series.nlargest([n, keep])	Return the largest *n* elements.
Series.nsmallest([n, keep])	Return the smallest *n* elements.
Series.pct_change([periods, fill_method, ...])	Percentage change between the current and a prior element.
Series.prod([axis, skipna, level, ...])	Return the product of the values over the requested axis.
Series.quantile([q, interpolation])	Return value at the given quantile.
Series.rank([axis, method, numeric_only, ...])	Compute numerical data ranks (1 through n) along axis.
Series.sem([axis, skipna, level, ddof, ...])	Return unbiased standard error of the mean over requested axis.
Series.skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis.
Series.std([axis, skipna, level, ddof, ...])	Return sample standard deviation over requested axis.
Series.sum([axis, skipna, level, ...])	Return the sum of the values over the requested axis.

continues on next page

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Series.var([axis, skipna, level, ddof, ...])	Return unbiased variance over requested axis.
Series.kurtosis([axis, skipna, level, ...])	Return unbiased kurtosis over requested axis.
Series.unique()	Return unique values of Series object.
Series.nunique([dropna])	Return number of unique elements in the object.
Series.is_unique	Return boolean if values in the object are unique.
Series.is_monotonic	Return boolean if values in the object are monotonic_increasing.
Series.is_monotonic_increasing	Alias for is_monotonic.
Series.is_monotonic_decreasing	Return boolean if values in the object are monotonic_decreasing.
Series.value_counts([normalize, sort, ...])	Return a Series containing counts of unique values.

3.3.8 Reindexing / selection / label manipulation

Series.align(other[, join, axis, level, ...])	Align two objects on their axes with the specified join method.
Series.drop([labels, axis, index, columns, ...])	Return Series with specified index labels removed.
Series.droplevel(level[, axis])	Return DataFrame with requested index / column level(s) removed.
Series.drop_duplicates([keep, inplace])	Return Series with duplicate values removed.
Series.duplicated([keep])	Indicate duplicate Series values.
Series.equals(other)	Test whether two objects contain the same elements.
Series.first(offset)	Select initial periods of time series data based on a date offset.
Series.head([n])	Return the first *n* rows.
Series.idxmax([axis, skipna])	Return the row label of the maximum value.
Series.idxmin([axis, skipna])	Return the row label of the minimum value.
Series.isin(values)	Whether elements in Series are contained in *values*.
Series.last(offset)	Select final periods of time series data based on a date offset.
Series.reindex([index])	Conform Series to new index with optional filling logic.
Series.reindex_like(other[, method, copy, ...])	Return an object with matching indices as other object.
Series.rename([index, axis, copy, inplace, ...])	Alter Series index labels or name.
Series.rename_axis([mapper, index, columns, ...])	Set the name of the axis for the index or columns.
Series.reset_index([level, drop, name, inplace])	Generate a new DataFrame or Series with the index reset.
Series.sample([n, frac, replace, weights, ...])	Return a random sample of items from an axis of object.
Series.set_axis(labels[, axis, inplace])	Assign desired index to given axis.
Series.take(indices[, axis, is_copy])	Return the elements in the given *positional* indices along an axis.
Series.tail([n])	Return the last *n* rows.
Series.truncate([before, after, axis, copy])	Truncate a Series or DataFrame before and after some index value.
Series.where(cond[, other, inplace, axis, ...])	Replace values where the condition is False.
Series.mask(cond[, other, inplace, axis, ...])	Replace values where the condition is True.
Series.add_prefix(prefix)	Prefix labels with string *prefix*.
Series.add_suffix(suffix)	Suffix labels with string *suffix*.

continues on next page

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Series.filter([items, like, regex, axis])	Subset the dataframe rows or columns according to the specified index labels.

3.3.9 Missing data handling

Series.backfill([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='bfill'.
Series.bfill([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='bfill'.
Series.dropna([axis, inplace, how])	Return a new Series with missing values removed.
Series.ffill([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='ffill'.
Series.fillna([value, method, axis, ...])	Fill NA/NaN values using the specified method.
Series.interpolate([method, axis, limit, ...])	Fill NaN values using an interpolation method.
Series.isna()	Detect missing values.
Series.isnull()	Detect missing values.
Series.notna()	Detect existing (non-missing) values.
Series.notnull()	Detect existing (non-missing) values.
Series.pad([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='ffill'.
Series.replace([to_replace, value, inplace, ...])	Replace values given in *to_replace* with *value*.

3.3.10 Reshaping, sorting

Series.argsort([axis, kind, order])	Return the integer indices that would sort the Series values.
Series.argmin([axis, skipna])	Return int position of the smallest value in the Series.
Series.argmax([axis, skipna])	Return int position of the largest value in the Series.
Series.reorder_levels(order)	Rearrange index levels using input order.
Series.sort_values([axis, ascending, ...])	Sort by the values.
Series.sort_index([axis, level, ascending, ...])	Sort Series by index labels.
Series.swaplevel([i, j, copy])	Swap levels i and j in a MultiIndex.
Series.unstack([level, fill_value])	Unstack, also known as pivot, Series with MultiIndex to produce DataFrame.
Series.explode([ignore_index])	Transform each element of a list-like to a row.
Series.searchsorted(value[, side, sorter])	Find indices where elements should be inserted to maintain order.
Series.ravel([order])	Return the flattened underlying data as an ndarray.
Series.repeat(repeats[, axis])	Repeat elements of a Series.
Series.squeeze([axis])	Squeeze 1 dimensional axis objects into scalars.
Series.view([dtype])	Create a new view of the Series.

3.3.11 Combining / comparing / joining / merging

Series.append(to_append[, ignore_index, ...])	Concatenate two or more Series.
Series.compare(other[, align_axis, ...])	Compare to another Series and show the differences.
Series.update(other)	Modify Series in place using values from passed Series.

3.3.12 Time Series-related

Series.asfreq(freq[, method, how, ...])	Convert TimeSeries to specified frequency.
Series.asof(where[, subset])	Return the last row(s) without any NaNs before *where*.
Series.shift([periods, freq, axis, fill_value])	Shift index by desired number of periods with an optional time *freq*.
Series.first_valid_index()	Return index for first non-NA/null value.
Series.last_valid_index()	Return index for last non-NA/null value.
Series.resample(rule[, axis, closed, label, ...])	Resample time-series data.
Series.tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
Series.tz_localize(tz[, axis, level, copy, ...])	Localize tz-naive index of a Series or DataFrame to target time zone.
Series.at_time(time[, asof, axis])	Select values at particular time of day (e.g., 9:30AM).
Series.between_time(start_time, end_time[, ...])	Select values between particular times of the day (e.g., 9:00-9:30 AM).
Series.tshift([periods, freq, axis])	(DEPRECATED) Shift the time index, using the index's frequency if available.
Series.slice_shift([periods, axis])	(DEPRECATED) Equivalent to *shift* without copying data.

3.3.13 Accessors

pandas provides dtype-specific methods under various accessors. These are separate namespaces within *Series* that only apply to specific data types.

Data Type	Accessor
Datetime, Timedelta, Period	*dt*
String	*str*
Categorical	*cat*
Sparse	*sparse*

Datetimelike properties

`Series.dt` can be used to access the values of the series as datetimelike and return several properties. These can be accessed like `Series.dt.<property>`.

Datetime properties

Series.dt.date	Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).
Series.dt.time	Returns numpy array of datetime.time.
Series.dt.timetz	Returns numpy array of datetime.time also containing timezone information.
Series.dt.year	The year of the datetime.
Series.dt.month	The month as January=1, December=12.
Series.dt.day	The day of the datetime.
Series.dt.hour	The hours of the datetime.
Series.dt.minute	The minutes of the datetime.
Series.dt.second	The seconds of the datetime.
Series.dt.microsecond	The microseconds of the datetime.
Series.dt.nanosecond	The nanoseconds of the datetime.
Series.dt.week	(DEPRECATED) The week ordinal of the year.
Series.dt.weekofyear	(DEPRECATED) The week ordinal of the year.
Series.dt.dayofweek	The day of the week with Monday=0, Sunday=6.
Series.dt.day_of_week	The day of the week with Monday=0, Sunday=6.
Series.dt.weekday	The day of the week with Monday=0, Sunday=6.
Series.dt.dayofyear	The ordinal day of the year.
Series.dt.day_of_year	The ordinal day of the year.
Series.dt.quarter	The quarter of the date.
Series.dt.is_month_start	Indicates whether the date is the first day of the month.
Series.dt.is_month_end	Indicates whether the date is the last day of the month.
Series.dt.is_quarter_start	Indicator for whether the date is the first day of a quarter.
Series.dt.is_quarter_end	Indicator for whether the date is the last day of a quarter.
Series.dt.is_year_start	Indicate whether the date is the first day of a year.
Series.dt.is_year_end	Indicate whether the date is the last day of the year.
Series.dt.is_leap_year	Boolean indicator if the date belongs to a leap year.
Series.dt.daysinmonth	The number of days in the month.
Series.dt.days_in_month	The number of days in the month.
Series.dt.tz	Return timezone, if any.
Series.dt.freq	Return the frequency object for this PeriodArray.

pandas.Series.dt.date

Series.dt.**date**
Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).

pandas.Series.dt.time

Series.dt.**time**
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.Series.dt.timetz

Series.dt.**timetz**
Returns numpy array of datetime.time also containing timezone information. The time part of the Timestamps.

pandas.Series.dt.year

Series.dt.**year**
The year of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="Y")
... )
>>> datetime_series
0   2000-12-31
1   2001-12-31
2   2002-12-31
dtype: datetime64[ns]
>>> datetime_series.dt.year
0    2000
1    2001
2    2002
dtype: int64
```

pandas.Series.dt.month

Series.dt.**month**
The month as January=1, December=12.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="M")
... )
>>> datetime_series
0   2000-01-31
1   2000-02-29
2   2000-03-31
dtype: datetime64[ns]
>>> datetime_series.dt.month
0    1
1    2
2    3
dtype: int64
```

pandas.Series.dt.day

Series.dt.**day**
The day of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="D")
... )
>>> datetime_series
0   2000-01-01
1   2000-01-02
2   2000-01-03
dtype: datetime64[ns]
>>> datetime_series.dt.day
0    1
1    2
2    3
dtype: int64
```

pandas.Series.dt.hour

Series.dt.**hour**
The hours of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="h")
... )
>>> datetime_series
0   2000-01-01 00:00:00
1   2000-01-01 01:00:00
2   2000-01-01 02:00:00
dtype: datetime64[ns]
>>> datetime_series.dt.hour
0    0
1    1
2    2
dtype: int64
```

pandas.Series.dt.minute

Series.dt.**minute**
The minutes of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="T")
... )
>>> datetime_series
0   2000-01-01 00:00:00
1   2000-01-01 00:01:00
2   2000-01-01 00:02:00
dtype: datetime64[ns]
>>> datetime_series.dt.minute
0    0
1    1
2    2
dtype: int64
```

pandas.Series.dt.second

Series.dt.**second**

The seconds of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="s")
... )
>>> datetime_series
0   2000-01-01 00:00:00
1   2000-01-01 00:00:01
2   2000-01-01 00:00:02
dtype: datetime64[ns]
>>> datetime_series.dt.second
0    0
1    1
2    2
dtype: int64
```

pandas.Series.dt.microsecond

Series.dt.**microsecond**

The microseconds of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="us")
... )
>>> datetime_series
0   2000-01-01 00:00:00.000000
1   2000-01-01 00:00:00.000001
2   2000-01-01 00:00:00.000002
dtype: datetime64[ns]
>>> datetime_series.dt.microsecond
0       0
1       1
2       2
dtype: int64
```

pandas.Series.dt.nanosecond

Series.dt.**nanosecond**
The nanoseconds of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="ns")
... )
>>> datetime_series
0   2000-01-01 00:00:00.000000000
1   2000-01-01 00:00:00.000000001
2   2000-01-01 00:00:00.000000002
dtype: datetime64[ns]
>>> datetime_series.dt.nanosecond
0       0
1       1
2       2
dtype: int64
```

pandas.Series.dt.week

Series.dt.**week**
The week ordinal of the year.

Deprecated since version 1.1.0.

Series.dt.weekofyear and Series.dt.week have been deprecated. Please use Series.dt.isocalendar().week instead.

pandas.Series.dt.weekofyear

Series.dt.**weekofyear**
The week ordinal of the year.

Deprecated since version 1.1.0.

Series.dt.weekofyear and Series.dt.week have been deprecated. Please use Series.dt.isocalendar().week instead.

pandas.Series.dt.dayofweek

Series.dt.**dayofweek**
The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the *dt* accessor) or DatetimeIndex.

Returns

Series or Index Containing integers indicating the day number.

See also:

Series.dt.dayofweek Alias.
Series.dt.weekday Alias.

Series.dt.day_name Returns the name of the day of the week.

Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

pandas.Series.dt.day_of_week

Series.dt.**day_of_week**

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the *dt* accessor) or DatetimeIndex.

Returns

Series or Index Containing integers indicating the day number.

See also:

Series.dt.dayofweek Alias.
Series.dt.weekday Alias.
Series.dt.day_name Returns the name of the day of the week.

Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

pandas.Series.dt.weekday

Series.dt.**weekday**
The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the *dt* accessor) or DatetimeIndex.

Returns

Series or Index Containing integers indicating the day number.

See also:

Series.dt.dayofweek Alias.
Series.dt.weekday Alias.
Series.dt.day_name Returns the name of the day of the week.

Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

pandas.Series.dt.dayofyear

Series.dt.**dayofyear**
The ordinal day of the year.

pandas.Series.dt.day_of_year

Series.dt.**day_of_year**
The ordinal day of the year.

pandas.Series.dt.quarter

Series.dt.**quarter**
The quarter of the date.

pandas.Series.dt.is_month_start

Series.dt.**is_month_start**

Indicates whether the date is the first day of the month.

Returns

Series or array For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

See also:

is_month_start Return a boolean indicating whether the date is the first day of the month.
is_month_end Return a boolean indicating whether the date is the last day of the month.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0   2018-02-27
1   2018-02-28
2   2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0    False
1    False
2    True
dtype: bool
>>> s.dt.is_month_end
0    False
1    True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

pandas.Series.dt.is_month_end

Series.dt.**is_month_end**

Indicates whether the date is the last day of the month.

Returns

Series or array For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

See also:

is_month_start Return a boolean indicating whether the date is the first day of the month.
is_month_end Return a boolean indicating whether the date is the last day of the month.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0   2018-02-27
1   2018-02-28
2   2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0    False
1    False
2    True
dtype: bool
>>> s.dt.is_month_end
0    False
1    True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

pandas.Series.dt.is_quarter_start

Series.dt.**is_quarter_start**

Indicator for whether the date is the first day of a quarter.

Returns

is_quarter_start [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.
is_quarter_end Similar property for indicating the quarter start.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                   periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...           is_quarter_start=df.dates.dt.is_quarter_start)
       dates  quarter  is_quarter_start
0 2017-03-30        1             False
1 2017-03-31        1             False
2 2017-04-01        2              True
3 2017-04-02        2             False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_start
array([False, False,  True, False])
```

pandas.Series.dt.is_quarter_end

`Series.dt.`**`is_quarter_end`**

Indicator for whether the date is the last day of a quarter.

Returns

is_quarter_end [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.
is_quarter_start Similar property indicating the quarter start.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                   periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...           is_quarter_end=df.dates.dt.is_quarter_end)
       dates  quarter    is_quarter_end
0 2017-03-30        1             False
1 2017-03-31        1              True
2 2017-04-01        2             False
3 2017-04-02        2             False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_end
array([False,  True, False, False])
```

pandas.Series.dt.is_year_start

Series.dt.**is_year_start**

Indicate whether the date is the first day of a year.

Returns

Series or DatetimeIndex The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

is_year_end Similar property indicating the last day of the year.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0   2017-12-30
1   2017-12-31
2   2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_start
0    False
1    False
2    True
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_start
array([False, False,  True])
```

pandas.Series.dt.is_year_end

Series.dt.**is_year_end**

Indicate whether the date is the last day of the year.

Returns

Series or DatetimeIndex The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

is_year_start Similar property indicating the start of the year.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0   2017-12-30
1   2017-12-31
2   2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_end
0    False
1     True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_end
array([False,  True, False])
```

pandas.Series.dt.is_leap_year

`Series.dt.`**`is_leap_year`**

Boolean indicator if the date belongs to a leap year.

A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not by 400.

Returns

Series or ndarray Booleans indicating if dates belong to a leap year.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
DatetimeIndex(['2012-12-31', '2013-12-31', '2014-12-31'],
              dtype='datetime64[ns]', freq='A-DEC')
>>> idx.is_leap_year
array([ True, False, False])
```

```
>>> dates_series = pd.Series(idx)
>>> dates_series
0   2012-12-31
1   2013-12-31
2   2014-12-31
dtype: datetime64[ns]
>>> dates_series.dt.is_leap_year
```

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```
0     True
1    False
2    False
dtype: bool
```

pandas.Series.dt.daysinmonth

Series.dt.**daysinmonth**
The number of days in the month.

pandas.Series.dt.days_in_month

Series.dt.**days_in_month**
The number of days in the month.

pandas.Series.dt.tz

Series.dt.**tz**
Return timezone, if any.

Returns

datetime.tzinfo, pytz.tzinfo.BaseTZInfo, dateutil.tz.tz.tzfile, or None Returns None when the array is tz-naive.

pandas.Series.dt.freq

Series.dt.**freq**

Datetime methods

Series.dt.to_period(*args, **kwargs)	Cast to PeriodArray/Index at a particular frequency.
Series.dt.to_pydatetime()	Return the data as an array of native Python datetime objects.
Series.dt.tz_localize(*args, **kwargs)	Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.
Series.dt.tz_convert(*args, **kwargs)	Convert tz-aware Datetime Array/Index from one time zone to another.
Series.dt.normalize(*args, **kwargs)	Convert times to midnight.
Series.dt.strftime(*args, **kwargs)	Convert to Index using specified date_format.
Series.dt.round(*args, **kwargs)	Perform round operation on the data to the specified *freq*.
Series.dt.floor(*args, **kwargs)	Perform floor operation on the data to the specified *freq*.
Series.dt.ceil(*args, **kwargs)	Perform ceil operation on the data to the specified *freq*.
Series.dt.month_name(*args, **kwargs)	Return the month names of the DateTimeIndex with specified locale.

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Series.dt.day_name(*args, **kwargs)	Return the day names of the DateTimeIndex with specified locale.

pandas.Series.dt.to_period

Series.dt.**to_period**(**args*, ***kwargs*)

Cast to PeriodArray/Index at a particular frequency.

Converts DatetimeArray/Index to PeriodArray/Index.

Parameters

freq [str or Offset, optional] One of pandas' *offset strings* or an Offset object. Will be inferred by default.

Returns

PeriodArray/Index

Raises

ValueError When converting a DatetimeArray/Index with non-regular values, so that a frequency cannot be inferred.

See also:

PeriodIndex Immutable ndarray holding ordinal values.
DatetimeIndex.to_pydatetime Return DatetimeIndex as object.

Examples

```
>>> df = pd.DataFrame({"y": [1, 2, 3]},
...                   index=pd.to_datetime(["2000-03-31 00:00:00",
...                                         "2000-05-31 00:00:00",
...                                         "2000-08-31 00:00:00"]))
>>> df.index.to_period("M")
PeriodIndex(['2000-03', '2000-05', '2000-08'],
            dtype='period[M]', freq='M')
```

Infer the daily frequency

```
>>> idx = pd.date_range("2017-01-01", periods=2)
>>> idx.to_period()
PeriodIndex(['2017-01-01', '2017-01-02'],
            dtype='period[D]', freq='D')
```

pandas.Series.dt.to_pydatetime

Series.dt.**to_pydatetime**()

Return the data as an array of native Python datetime objects.

Timezone information is retained if present.

Warning: Python's datetime uses microsecond resolution, which is lower than pandas (nanosecond). The values are truncated.

Returns

numpy.ndarray Object dtype array containing native Python datetime objects.

See also:

`datetime.datetime` Standard library value for a datetime.

Examples

```
>>> s = pd.Series(pd.date_range('20180310', periods=2))
>>> s
0   2018-03-10
1   2018-03-11
dtype: datetime64[ns]
```

```
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0),
       datetime.datetime(2018, 3, 11, 0, 0)], dtype=object)
```

pandas' nanosecond precision is truncated to microseconds.

```
>>> s = pd.Series(pd.date_range('20180310', periods=2, freq='ns'))
>>> s
0   2018-03-10 00:00:00.000000000
1   2018-03-10 00:00:00.000000001
dtype: datetime64[ns]
```

```
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0),
       datetime.datetime(2018, 3, 10, 0, 0)], dtype=object)
```

pandas.Series.dt.tz_localize

`Series.dt.`**`tz_localize`**`(*args, **kwargs)`

Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.

This method takes a time zone (tz) naive Datetime Array/Index object and makes this time zone aware. It does not move the time to another time zone. Time zone localization helps to switch from time zone aware to time zone unaware objects.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone to convert timestamps to. Passing `None` will remove the time zone information preserving local time.

ambiguous ['infer', 'NaT', bool array, default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times

- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

nonexistent ['shift_forward', 'shift_backward, 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

Same type as self Array/Index converted to the specified time zone.

Raises

TypeError If the Datetime Array/Index is tz-aware and tz is not None.

See also:

DatetimeIndex.tz_convert Convert tz-aware DatetimeIndex from one time zone to another.

Examples

```
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq='D')
```

Localize DatetimeIndex in US/Eastern time zone:

```
>>> tz_aware = tz_naive.tz_localize(tz='US/Eastern')
>>> tz_aware
DatetimeIndex(['2018-03-01 09:00:00-05:00',
               '2018-03-02 09:00:00-05:00',
               '2018-03-03 09:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

With the `tz=None`, we can remove the time zone information while keeping the local time (not converted to UTC):

```
>>> tz_aware.tz_localize(None)
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:30:00',
...                               '2018-10-28 02:00:00',
...                               '2018-10-28 02:30:00',
```

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```
...                                 '2018-10-28 02:00:00',
...                                 '2018-10-28 02:30:00',
...                                 '2018-10-28 03:00:00',
...                                 '2018-10-28 03:30:00']))
>>> s.dt.tz_localize('CET', ambiguous='infer')
0   2018-10-28 01:30:00+02:00
1   2018-10-28 02:00:00+02:00
2   2018-10-28 02:30:00+02:00
3   2018-10-28 02:00:00+01:00
4   2018-10-28 02:30:00+01:00
5   2018-10-28 03:00:00+01:00
6   2018-10-28 03:30:00+01:00
dtype: datetime64[ns, CET]
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:20:00',
...                                 '2018-10-28 02:36:00',
...                                 '2018-10-28 03:46:00']))
>>> s.dt.tz_localize('CET', ambiguous=np.array([True, True, False]))
0   2018-10-28 01:20:00+02:00
1   2018-10-28 02:36:00+02:00
2   2018-10-28 03:46:00+01:00
dtype: datetime64[ns, CET]
```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a timedelta object or *'shift_forward'* or *'shift_backwards'*.

```
>>> s = pd.to_datetime(pd.Series(['2015-03-29 02:30:00',
...                                 '2015-03-29 03:30:00']))
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
0   2015-03-29 03:00:00+02:00
1   2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]
```

```
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
0   2015-03-29 01:59:59.999999999+01:00
1   2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]
```

```
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
0   2015-03-29 03:30:00+02:00
1   2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]
```

pandas.Series.dt.tz_convert

Series.dt.**tz_convert**(**args*, ***kwargs*)

Convert tz-aware Datetime Array/Index from one time zone to another.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time. Corresponding timestamps would be converted to this time zone of the Datetime Array/Index. A *tz* of None will convert to UTC and remove the timezone information.

Returns

Array or Index

Raises

TypeError If Datetime Array/Index is tz-naive.

See also:

DatetimeIndex.tz A timezone that has a variable offset from UTC.

DatetimeIndex.tz_localize Localize tz-naive DatetimeIndex to a given time zone, or remove timezone from a tz-aware DatetimeIndex.

Examples

With the *tz* parameter, we can change the DatetimeIndex to other time zones:

```
>>> dti = pd.date_range(start='2014-08-01 09:00',
...                     freq='H', periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
              dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
               '2014-08-01 03:00:00-05:00',
               '2014-08-01 04:00:00-05:00'],
              dtype='datetime64[ns, US/Central]', freq='H')
```

With the `tz=None`, we can remove the timezone (after converting to UTC if necessary):

```
>>> dti = pd.date_range(start='2014-08-01 09:00', freq='H',
...                     periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
                dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
               '2014-08-01 08:00:00',
```

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```
               '2014-08-01 09:00:00'],
                dtype='datetime64[ns]', freq='H')
```

pandas.Series.dt.normalize

Series.dt.**normalize**(**args*, ***kwargs*)

Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the `.dt` accessor, and directly on Datetime Array/Index.

Returns

DatetimeArray, DatetimeIndex or Series The same type as the original data. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

floor Floor the datetimes to the specified freq.
ceil Ceil the datetimes to the specified freq.
round Round the datetimes to the specified freq.

Examples

```
>>> idx = pd.date_range(start='2014-08-01 10:00', freq='H',
...                     periods=3, tz='Asia/Calcutta')
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
               '2014-08-01 11:00:00+05:30',
               '2014-08-01 12:00:00+05:30'],
                dtype='datetime64[ns, Asia/Calcutta]', freq='H')
>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30'],
              dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

pandas.Series.dt.strftime

Series.dt.**strftime**(**args*, ***kwargs*)

Convert to Index using specified date_format.

Return an Index of formatted strings specified by date_format, which supports the same string format as the python standard library. Details of the string format can be found in python string format doc.

Parameters

date_format [str] Date format string (e.g. "%Y-%m-%d").

Returns

ndarray NumPy ndarray of formatted strings.

See also:

to_datetime Convert the given argument to datetime.
DatetimeIndex.normalize Return DatetimeIndex with times to midnight.
DatetimeIndex.round Round the DatetimeIndex to the specified freq.
DatetimeIndex.floor Floor the DatetimeIndex to the specified freq.

Examples

```
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                     periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
       'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

pandas.Series.dt.round

Series.dt.**round**(**args*, ***kwargs*)

Perform round operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to round the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.round("H")
0   2018-01-01 12:00:00
1   2018-01-01 12:00:00
2   2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.Series.dt.floor

Series.dt.**floor**(**args*, ***kwargs*)

Perform floor operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta

- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.floor("H")
0   2018-01-01 11:00:00
1   2018-01-01 12:00:00
2   2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.Series.dt.ceil

Series.dt.**ceil**(**args*, ***kwargs*)

Perform ceil operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.ceil("H")
0   2018-01-01 12:00:00
1   2018-01-01 12:00:00
2   2018-01-01 13:00:00
dtype: datetime64[ns]
```

pandas.Series.dt.month_name

Series.dt.**month_name**(**args*, ***kwargs*)

Return the month names of the DateTimeIndex with specified locale.

Parameters

locale [str, optional] Locale determining the language in which to return the month name. Default is English locale.

Returns

Index Index of month names.

Examples

```
>>> idx = pd.date_range(start='2018-01', freq='M', periods=3)
>>> idx
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31'],
              dtype='datetime64[ns]', freq='M')
>>> idx.month_name()
Index(['January', 'February', 'March'], dtype='object')
```

pandas.Series.dt.day_name

Series.dt.**day_name**(**args*, ***kwargs*)

Return the day names of the DateTimeIndex with specified locale.

Parameters

locale [str, optional] Locale determining the language in which to return the day name. Default is English locale.

Returns

Index Index of day names.

Examples

```
>>> idx = pd.date_range(start='2018-01-01', freq='D', periods=3)
>>> idx
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03'],
              dtype='datetime64[ns]', freq='D')
>>> idx.day_name()
Index(['Monday', 'Tuesday', 'Wednesday'], dtype='object')
```

Period properties

Series.dt.qyear
Series.dt.start_time
Series.dt.end_time

pandas.Series.dt.qyear

Series.dt.**qyear**

pandas.Series.dt.start_time

Series.dt.**start_time**

pandas.Series.dt.end_time

Series.dt.**end_time**

Timedelta properties

Series.dt.days	Number of days for each element.
Series.dt.seconds	Number of seconds (>= 0 and less than 1 day) for each element.
Series.dt.microseconds	Number of microseconds (>= 0 and less than 1 second) for each element.
Series.dt.nanoseconds	Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
Series.dt.components	Return a Dataframe of the components of the Timedeltas.

pandas.Series.dt.days

Series.dt.**days**
Number of days for each element.

pandas.Series.dt.seconds

Series.dt.**seconds**
Number of seconds (>= 0 and less than 1 day) for each element.

pandas.Series.dt.microseconds

Series.dt.**microseconds**
Number of microseconds (>= 0 and less than 1 second) for each element.

pandas.Series.dt.nanoseconds

Series.dt.**nanoseconds**
Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

pandas.Series.dt.components

Series.dt.**components**

Return a Dataframe of the components of the Timedeltas.

Returns

DataFrame

Examples

```
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='s'))
>>> s
0   0 days 00:00:00
1   0 days 00:00:01
2   0 days 00:00:02
3   0 days 00:00:03
4   0 days 00:00:04
dtype: timedelta64[ns]
>>> s.dt.components
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0     0      0        0        0             0             0            0
1     0      0        0        1             0             0            0
2     0      0        0        2             0             0            0
3     0      0        0        3             0             0            0
4     0      0        0        4             0             0            0
```

Timedelta methods

Series.dt.to_pytimedelta()	Return an array of native *datetime.timedelta* objects.
Series.dt.total_seconds(*args, **kwargs)	Return total duration of each element expressed in seconds.

pandas.Series.dt.to_pytimedelta

Series.dt.**to_pytimedelta**()

Return an array of native *datetime.timedelta* objects.

Python's standard *datetime* library uses a different representation timedelta's. This method converts a Series of pandas Timedeltas to *datetime.timedelta* format with the same length as the original Series.

Returns

numpy.ndarray Array of 1D containing data with *datetime.timedelta* type.

See also:

datetime.timedelta A duration expressing the difference between two date, time, or datetime.

Examples

```
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit="d"))
>>> s
0   0 days
1   1 days
2   2 days
3   3 days
4   4 days
dtype: timedelta64[ns]
```

```
>>> s.dt.to_pytimedelta()
array([datetime.timedelta(0), datetime.timedelta(days=1),
datetime.timedelta(days=2), datetime.timedelta(days=3),
datetime.timedelta(days=4)], dtype=object)
```

pandas.Series.dt.total_seconds

Series.dt.**total_seconds**(**args*, ***kwargs*)

Return total duration of each element expressed in seconds.

This method is available directly on TimedeltaArray, TimedeltaIndex and on Series containing timedelta values under the `.dt` namespace.

Returns

seconds [[ndarray, Float64Index, Series]] When the calling object is a TimedeltaArray, the return type is ndarray. When the calling object is a TimedeltaIndex, the return type is a Float64Index. When the calling object is a Series, the return type is Series of type *float64* whose index is the same as the original.

See also:

datetime.timedelta.total_seconds Standard library version of this method.
TimedeltaIndex.components Return a DataFrame with components of each Timedelta.

Examples

Series

```
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='d'))
>>> s
0   0 days
1   1 days
2   2 days
3   3 days
4   4 days
dtype: timedelta64[ns]
```

```
>>> s.dt.total_seconds()
0         0.0
1     86400.0
2    172800.0
3    259200.0
4    345600.0
dtype: float64
```

TimedeltaIndex

```
>>> idx = pd.to_timedelta(np.arange(5), unit='d')
>>> idx
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq=None)
```

```
>>> idx.total_seconds()
Float64Index([0.0, 86400.0, 172800.0, 259200.00000000003, 345600.0],
             dtype='float64')
```

String handling

`Series.str` can be used to access the values of the series as strings and apply several methods to it. These can be accessed like `Series.str.<function/property>`.

Series.str.capitalize()	Convert strings in the Series/Index to be capitalized.
Series.str.casefold()	Convert strings in the Series/Index to be casefolded.
Series.str.cat([others, sep, na_rep, join])	Concatenate strings in the Series/Index with given separator.
Series.str.center(width[, fillchar])	Pad left and right side of strings in the Series/Index.
Series.str.contains(pat[, case, flags, na, ...])	Test if pattern or regex is contained within a string of a Series or Index.
Series.str.count(pat[, flags])	Count occurrences of pattern in each string of the Series/Index.
Series.str.decode(encoding[, errors])	Decode character string in the Series/Index using indicated encoding.
Series.str.encode(encoding[, errors])	Encode character string in the Series/Index using indicated encoding.
Series.str.endswith(pat[, na])	Test if the end of each string element matches a pattern.
Series.str.extract(pat[, flags, expand])	Extract capture groups in the regex *pat* as columns in a DataFrame.
Series.str.extractall(pat[, flags])	Extract capture groups in the regex *pat* as columns in DataFrame.
Series.str.find(sub[, start, end])	Return lowest indexes in each strings in the Series/Index.
Series.str.findall(pat[, flags])	Find all occurrences of pattern or regular expression in the Series/Index.
Series.str.get(i)	Extract element from each component at specified position.
Series.str.index(sub[, start, end])	Return lowest indexes in each string in Series/Index.
Series.str.join(sep)	Join lists contained as elements in the Series/Index with passed delimiter.
Series.str.len()	Compute the length of each element in the Series/Index.
Series.str.ljust(width[, fillchar])	Pad right side of strings in the Series/Index.
Series.str.lower()	Convert strings in the Series/Index to lowercase.
Series.str.lstrip([to_strip])	Remove leading characters.
Series.str.match(pat[, case, flags, na])	Determine if each string starts with a match of a regular expression.
Series.str.normalize(form)	Return the Unicode normal form for the strings in the Series/Index.

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Series.str.pad(width[, side, fillchar])	Pad strings in the Series/Index up to width.
Series.str.partition([sep, expand])	Split the string at the first occurrence of *sep*.
Series.str.repeat(repeats)	Duplicate each string in the Series or Index.
Series.str.replace(pat, repl[, n, case, ...])	Replace each occurrence of pattern/regex in the Series/Index.
Series.str.rfind(sub[, start, end])	Return highest indexes in each strings in the Series/Index.
Series.str.rindex(sub[, start, end])	Return highest indexes in each string in Series/Index.
Series.str.rjust(width[, fillchar])	Pad left side of strings in the Series/Index.
Series.str.rpartition([sep, expand])	Split the string at the last occurrence of *sep*.
Series.str.rstrip([to_strip])	Remove trailing characters.
Series.str.slice([start, stop, step])	Slice substrings from each element in the Series or Index.
Series.str.slice_replace([start, stop, repl])	Replace a positional slice of a string with another value.
Series.str.split([pat, n, expand])	Split strings around given separator/delimiter.
Series.str.rsplit([pat, n, expand])	Split strings around given separator/delimiter.
Series.str.startswith(pat[, na])	Test if the start of each string element matches a pattern.
Series.str.strip([to_strip])	Remove leading and trailing characters.
Series.str.swapcase()	Convert strings in the Series/Index to be swapcased.
Series.str.title()	Convert strings in the Series/Index to titlecase.
Series.str.translate(table)	Map all characters in the string through the given mapping table.
Series.str.upper()	Convert strings in the Series/Index to uppercase.
Series.str.wrap(width, **kwargs)	Wrap strings in Series/Index at specified line width.
Series.str.zfill(width)	Pad strings in the Series/Index by prepending '0' characters.
Series.str.isalnum()	Check whether all characters in each string are alphanumeric.
Series.str.isalpha()	Check whether all characters in each string are alphabetic.
Series.str.isdigit()	Check whether all characters in each string are digits.
Series.str.isspace()	Check whether all characters in each string are alphanumeric.
Series.str.islower()	Check whether all characters in each string are lowercase.
Series.str.isupper()	Check whether all characters in each string are uppercase.
Series.str.istitle()	Check whether all characters in each string are titlecase.
Series.str.isnumeric()	Check whether all characters in each string are numeric.
Series.str.isdecimal()	Check whether all characters in each string are decimal.
Series.str.get_dummies([sep])	Return DataFrame of dummy/indicator variables for Series.

pandas.Series.str.capitalize

Series.str.**capitalize**()

Convert strings in the Series/Index to be capitalized.

Equivalent to `str.capitalize()`.

Returns

Series or Index of object

See also:

Series.str.lower	Converts all characters to lowercase.
Series.str.upper	Converts all characters to uppercase.
Series.str.title	Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize	Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase	Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold	Removes all case distinctions in the string.

Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0                 lower
1              CAPITALS
2    this is a sentence
3              SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0                 lower
1              capitals
2    this is a sentence
3              swapcase
dtype: object
```

```
>>> s.str.upper()
0                 LOWER
1              CAPITALS
2    THIS IS A SENTENCE
3              SWAPCASE
dtype: object
```

```
>>> s.str.title()
0                 Lower
1              Capitals
2    This Is A Sentence
3              Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0                 Lower
1              Capitals
2    This is a sentence
3              Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0                 LOWER
1              capitals
2    THIS IS A SENTENCE
3              sWaPcAsE
dtype: object
```

pandas.Series.str.casefold

Series.str.**casefold**()

Convert strings in the Series/Index to be casefolded.

New in version 0.25.0.

Equivalent to `str.casefold()`.

Returns

Series or Index of object

See also:

Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold Removes all case distinctions in the string.

Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0                 lower
1              CAPITALS
2    this is a sentence
3              SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0                 lower
1              capitals
2    this is a sentence
3              swapcase
dtype: object
```

```
>>> s.str.upper()
0                 LOWER
1              CAPITALS
2    THIS IS A SENTENCE
3              SWAPCASE
dtype: object
```

```
>>> s.str.title()
0                 Lower
```

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```
1              Capitals
2    This Is A Sentence
3              Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0                 Lower
1              Capitals
2    This is a sentence
3              Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0                 LOWER
1              capitals
2    THIS IS A SENTENCE
3              sWaPcAsE
dtype: object
```

pandas.Series.str.cat

Series.str.**cat**(*others=None*, *sep=None*, *na_rep=None*, *join='left'*)

Concatenate strings in the Series/Index with given separator.

If *others* is specified, this function concatenates the Series/Index and elements of *others* element-wise. If *others* is not passed, then all values in the Series/Index are concatenated into a single string with a given *sep*.

Parameters

others [Series, Index, DataFrame, np.ndarray or list-like] Series, Index, DataFrame, np.ndarray (one- or two-dimensional) and other list-likes of strings must have the same length as the calling Series/Index, with the exception of indexed objects (i.e. Series/Index/DataFrame) if *join* is not None.

If others is a list-like that contains a combination of Series, Index or np.ndarray (1-dim), then all elements will be unpacked and must satisfy the above criteria individually.

If others is None, the method returns the concatenation of all strings in the calling Series/Index.

sep [str, default ‘’] The separator between the different elements/columns. By default the empty string ‘’ is used.

na_rep [str or None, default None] Representation that is inserted for all missing values:

- If *na_rep* is None, and *others* is None, missing values in the Series/Index are omitted from the result.
- If *na_rep* is None, and *others* is not None, a row containing a missing value in any of the columns (before concatenation) will have a missing value in the result.

join [{‘left’, ‘right’, ‘outer’, ‘inner’}, default ‘left’] Determines the join-style between the calling Series/Index and any Series/Index/DataFrame in *others* (objects without an index need to match the length of the calling Series/Index). To disable alignment, use *.values* on any Series/Index/DataFrame in *others*.

New in version 0.23.0.

Changed in version 1.0.0: Changed default of *join* from None to *‘left’*.

Returns

str, Series or Index If *others* is None, *str* is returned, otherwise a *Series/Index* (same type as caller) of objects is returned.

See also:

split Split each string in the Series/Index.
join Join lists contained as elements in the Series/Index.

Examples

When not passing *others*, all values are concatenated into a single string:

```
>>> s = pd.Series(['a', 'b', np.nan, 'd'])
>>> s.str.cat(sep=' ')
'a b d'
```

By default, NA values in the Series are ignored. Using *na_rep*, they can be given a representation:

```
>>> s.str.cat(sep=' ', na_rep='?')
'a b ? d'
```

If *others* is specified, corresponding values are concatenated with the separator. Result will be a Series of strings.

```
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=',')
0    a,A
1    b,B
2    NaN
3    d,D
dtype: object
```

Missing values will remain missing in the result, but can again be represented using *na_rep*

```
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=',', na_rep='-')
0    a,A
1    b,B
2    -,C
3    d,D
dtype: object
```

If *sep* is not specified, the values are concatenated without separation.

```
>>> s.str.cat(['A', 'B', 'C', 'D'], na_rep='-')
0    aA
1    bB
2    -C
3    dD
dtype: object
```

Series with different indexes can be aligned before concatenation. The *join*-keyword works as in other methods.

```
>>> t = pd.Series(['d', 'a', 'e', 'c'], index=[3, 0, 4, 2])
>>> s.str.cat(t, join='left', na_rep='-')
0    aa
1    b-
2    -c
3    dd
```

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```
dtype: object
>>>
>>> s.str.cat(t, join='outer', na_rep='-')
0    aa
1    b-
2    -c
3    dd
4    -e
dtype: object
>>>
>>> s.str.cat(t, join='inner', na_rep='-')
0    aa
2    -c
3    dd
dtype: object
>>>
>>> s.str.cat(t, join='right', na_rep='-')
3    dd
0    aa
4    -e
2    -c
dtype: object
```

For more examples, see *here*.

pandas.Series.str.center

`Series.str.`**`center`**(*width*, *fillchar=' '*)

Pad left and right side of strings in the Series/Index.

Equivalent to `str.center()`.

Parameters

width [int] Minimum width of resulting string; additional characters will be filled with `fillchar`.

fillchar [str] Additional character for filling, default is whitespace.

Returns

filled [Series/Index of objects.]

pandas.Series.str.contains

`Series.str.`**`contains`**(*pat*, *case=True*, *flags=0*, *na=None*, *regex=True*)

Test if pattern or regex is contained within a string of a Series or Index.

Return boolean Series or Index based on whether a given pattern or regex is contained within a string of a Series or Index.

Parameters

pat [str] Character sequence or regular expression.

case [bool, default True] If True, case sensitive.

flags [int, default 0 (no flags)] Flags to pass through to the re module, e.g. re.IGNORECASE.

na [scalar, optional] Fill value for missing values. The default depends on dtype of the array. For object-dtype, `numpy.nan` is used. For `StringDtype`, `pandas.NA` is used.

regex [bool, default True] If True, assumes the pat is a regular expression.

If False, treats the pat as a literal string.

Returns

Series or Index of boolean values A Series or Index of boolean values indicating whether the given pattern is contained within the string of each element of the Series or Index.

See also:

match Analogous, but stricter, relying on re.match instead of re.search.
Series.str.startswith Test if the start of each string element matches a pattern.
Series.str.endswith Same as startswith, but tests the end of string.

Examples

Returning a Series of booleans using only a literal pattern.

```
>>> s1 = pd.Series(['Mouse', 'dog', 'house and parrot', '23', np.NaN])
>>> s1.str.contains('og', regex=False)
0    False
1     True
2    False
3    False
4      NaN
dtype: object
```

Returning an Index of booleans using only a literal pattern.

```
>>> ind = pd.Index(['Mouse', 'dog', 'house and parrot', '23.0', np.NaN])
>>> ind.str.contains('23', regex=False)
Index([False, False, False, True, nan], dtype='object')
```

Specifying case sensitivity using *case*.

```
>>> s1.str.contains('oG', case=True, regex=True)
0    False
1    False
2    False
3    False
4      NaN
dtype: object
```

Specifying *na* to be *False* instead of *NaN* replaces NaN values with *False*. If Series or Index does not contain NaN values the resultant dtype will be *bool*, otherwise, an *object* dtype.

```
>>> s1.str.contains('og', na=False, regex=True)
0    False
1     True
2    False
3    False
4    False
dtype: bool
```

Returning ‘house’ or ‘dog’ when either expression occurs in a string.

```
>>> s1.str.contains('house|dog', regex=True)
0    False
1     True
2     True
3    False
4      NaN
dtype: object
```

Ignoring case sensitivity using *flags* with regex.

```
>>> import re
>>> s1.str.contains('PARROT', flags=re.IGNORECASE, regex=True)
0    False
1    False
2     True
3    False
4      NaN
dtype: object
```

Returning any digit using regular expression.

```
>>> s1.str.contains('\\d', regex=True)
0    False
1    False
2    False
3     True
4      NaN
dtype: object
```

Ensure *pat* is a not a literal pattern when *regex* is set to True. Note in the following example one might expect only *s2[1]* and *s2[3]* to return *True*. However, '.0' as a regex matches any character followed by a 0.

```
>>> s2 = pd.Series(['40', '40.0', '41', '41.0', '35'])
>>> s2.str.contains('.0', regex=True)
0     True
1     True
2    False
3     True
4    False
dtype: bool
```

pandas.Series.str.count

`Series.str.`**`count`**(*pat*, *flags=0*)

Count occurrences of pattern in each string of the Series/Index.

This function is used to count the number of times a particular regex pattern is repeated in each of the string elements of the *Series*.

Parameters

pat [str] Valid regular expression.

flags [int, default 0, meaning no flags] Flags for the *re* module. For a complete list, see here.

****kwargs** For compatibility with other string methods. Not used.

Returns

Series or Index Same type as the calling object containing the integer counts.

See also:

`re` Standard library module for regular expressions.
`str.count` Standard library version, without regular expression support.

Notes

Some characters need to be escaped when passing in *pat*. eg. `'$'` has a special meaning in regex and must be escaped when finding this literal character.

Examples

```
>>> s = pd.Series(['A', 'B', 'Aaba', 'Baca', np.nan, 'CABA', 'cat'])
>>> s.str.count('a')
0    0.0
1    0.0
2    2.0
3    2.0
4    NaN
5    0.0
6    1.0
dtype: float64
```

Escape `'$'` to find the literal dollar sign.

```
>>> s = pd.Series(['$', 'B', 'Aab$', '$$ca', 'C$B$', 'cat'])
>>> s.str.count('\\$')
0    1
1    0
2    1
3    2
4    2
5    0
dtype: int64
```

This is also available on Index

```
>>> pd.Index(['A', 'A', 'Aaba', 'cat']).str.count('a')
Int64Index([0, 0, 2, 1], dtype='int64')
```

pandas.Series.str.decode

`Series.str.`**`decode`**(*encoding*, *errors='strict'*)

Decode character string in the Series/Index using indicated encoding.

Equivalent to `str.decode()` in python2 and `bytes.decode()` in python3.

Parameters

encoding [str]

errors [str, optional]

Returns

Series or Index

pandas.Series.str.encode

Series.str.**encode**(*encoding*, *errors='strict'*)

Encode character string in the Series/Index using indicated encoding.

Equivalent to `str.encode()`.

Parameters

encoding [str]

errors [str, optional]

Returns

encoded [Series/Index of objects]

pandas.Series.str.endswith

Series.str.**endswith**(*pat*, *na=None*)

Test if the end of each string element matches a pattern.

Equivalent to `str.endswith()`.

Parameters

pat [str] Character sequence. Regular expressions are not accepted.

na [object, default NaN] Object shown if element tested is not a string. The default depends on dtype of the array. For object-dtype, `numpy.nan` is used. For `StringDtype`, `pandas.NA` is used.

Returns

Series or Index of bool A Series of booleans indicating whether the given pattern matches the end of each string element.

See also:

str.endswith Python standard library string method.
Series.str.startswith Same as endswith, but tests the start of string.
Series.str.contains Tests if string element contains a pattern.

Examples

```
>>> s = pd.Series(['bat', 'bear', 'caT', np.nan])
>>> s
0     bat
1    bear
2     caT
3     NaN
dtype: object
```

```
>>> s.str.endswith('t')
0     True
1    False
2    False
3      NaN
dtype: object
```

Specifying *na* to be *False* instead of *NaN*.

```
>>> s.str.endswith('t', na=False)
0     True
1    False
2    False
3    False
dtype: bool
```

pandas.Series.str.extract

Series.str.**extract**(*pat*, *flags=0*, *expand=True*)

Extract capture groups in the regex *pat* as columns in a DataFrame.

For each subject string in the Series, extract groups from the first match of regular expression *pat*.

Parameters

pat [str] Regular expression pattern with capturing groups.

flags [int, default 0 (no flags)] Flags from the `re` module, e.g. `re.IGNORECASE`, that modify regular expression matching for things like case, spaces, etc. For more details, see `re`.

expand [bool, default True] If True, return DataFrame with one column per capture group. If False, return a Series/Index if there is one capture group or DataFrame if there are multiple capture groups.

Returns

DataFrame or Series or Index A DataFrame with one row for each subject string, and one column for each group. Any capture group names in regular expression pat will be used for column names; otherwise capture group numbers will be used. The dtype of each result column is always object, even when no match is found. If `expand=False` and pat has only one capture group, then return a Series (if subject is a Series) or Index (if subject is an Index).

See also:

extractall Returns all matches (not just the first match).

Examples

A pattern with two groups will return a DataFrame with two columns. Non-matches will be NaN.

```
>>> s = pd.Series(['a1', 'b2', 'c3'])
>>> s.str.extract(r'([ab])(\d)')
     0    1
0    a    1
1    b    2
2  NaN  NaN
```

A pattern may contain optional groups.

```
>>> s.str.extract(r'([ab])?(\d)')
     0  1
0    a  1
1    b  2
2  NaN  3
```

Named groups will become column names in the result.

```
>>> s.str.extract(r'(?P<letter>[ab])(?P<digit>\d)')
letter digit
0      a     1
1      b     2
2    NaN   NaN
```

A pattern with one group will return a DataFrame with one column if expand=True.

```
>>> s.str.extract(r'[ab](\d)', expand=True)
    0
0   1
1   2
2 NaN
```

A pattern with one group will return a Series if expand=False.

```
>>> s.str.extract(r'[ab](\d)', expand=False)
0      1
1      2
2    NaN
dtype: object
```

pandas.Series.str.extractall

`Series.str.`**`extractall`**(*pat*, *flags=0*)

Extract capture groups in the regex *pat* as columns in DataFrame.

For each subject string in the Series, extract groups from all matches of regular expression pat. When each subject string in the Series has exactly one match, extractall(pat).xs(0, level='match') is the same as extract(pat).

Parameters

pat [str] Regular expression pattern with capturing groups.

flags [int, default 0 (no flags)] A `re` module flag, for example `re.IGNORECASE`. These allow to modify regular expression matching for things like case, spaces, etc. Multiple flags can be combined with the bitwise OR operator, for example `re.IGNORECASE | re.MULTILINE`.

Returns

DataFrame A `DataFrame` with one row for each match, and one column for each group. Its rows have a `MultiIndex` with first levels that come from the subject `Series`. The last level is named 'match' and indexes the matches in each item of the `Series`. Any capture group names in regular expression pat will be used for column names; otherwise capture group numbers will be used.

See also:

extract Returns first match only (not all matches).

Examples

A pattern with one group will return a DataFrame with one column. Indices with no matches will not appear in the result.

```
>>> s = pd.Series(["a1a2", "b1", "c1"], index=["A", "B", "C"])
>>> s.str.extractall(r"[ab](\d)")
        0
match
A 0     1
1     2
B 0     1
```

Capture group names are used for column names of the result.

```
>>> s.str.extractall(r"[ab](?P<digit>\d)")
        digit
match
A 0         1
1         2
B 0         1
```

A pattern with two groups will return a DataFrame with two columns.

```
>>> s.str.extractall(r"(?P<letter>[ab])(?P<digit>\d)")
        letter digit
match
A 0          a     1
1          a     2
B 0          b     1
```

Optional groups that do not match are NaN in the result.

```
>>> s.str.extractall(r"(?P<letter>[ab])?(?P<digit>\d)")
        letter digit
match
A 0          a     1
1          a     2
B 0          b     1
C 0        NaN     1
```

pandas.Series.str.find

Series.str.**find**(*sub*, *start=0*, *end=None*)

Return lowest indexes in each strings in the Series/Index.

Each of returned indexes corresponds to the position where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.find()`.

Parameters

sub [str] Substring being searched.

start [int] Left edge index.

end [int] Right edge index.

Returns

Series or Index of int.

See also:

rfind Return highest indexes in each strings.

pandas.Series.str.findall

Series.str.**findall**(*pat*, *flags=0*)

Find all occurrences of pattern or regular expression in the Series/Index.

Equivalent to applying `re.findall()` to all the elements in the Series/Index.

Parameters

pat [str] Pattern or regular expression.

flags [int, default 0] Flags from `re` module, e.g. *re.IGNORECASE* (default is 0, which means no flags).

Returns

Series/Index of lists of strings All non-overlapping matches of pattern or regular expression in each string of this Series/Index.

See also:

count Count occurrences of pattern or regular expression in each string of the Series/Index.

extractall For each string in the Series, extract groups from all matches of regular expression and return a DataFrame with one row for each match and one column for each group.

re.findall The equivalent `re` function to all non-overlapping matches of pattern or regular expression in string, as a list of strings.

Examples

```
>>> s = pd.Series(['Lion', 'Monkey', 'Rabbit'])
```

The search for the pattern 'Monkey' returns one match:

```
>>> s.str.findall('Monkey')
0          []
1    [Monkey]
2          []
dtype: object
```

On the other hand, the search for the pattern 'MONKEY' doesn't return any match:

```
>>> s.str.findall('MONKEY')
0    []
1    []
2    []
dtype: object
```

Flags can be added to the pattern or regular expression. For instance, to find the pattern 'MONKEY' ignoring the case:

```
>>> import re
>>> s.str.findall('MONKEY', flags=re.IGNORECASE)
0          []
```

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```
1    [Monkey]
2          []
dtype: object
```

When the pattern matches more than one string in the Series, all matches are returned:

```
>>> s.str.findall('on')
0    [on]
1    [on]
2      []
dtype: object
```

Regular expressions are supported too. For instance, the search for all the strings ending with the word 'on' is shown next:

```
>>> s.str.findall('on$')
0    [on]
1      []
2      []
dtype: object
```

If the pattern is found more than once in the same string, then a list of multiple strings is returned:

```
>>> s.str.findall('b')
0        []
1        []
2    [b, b]
dtype: object
```

pandas.Series.str.get

`Series.str.get(i)`

Extract element from each component at specified position.

Extract element from lists, tuples, or strings in each element in the Series/Index.

Parameters

i [int] Position of element to extract.

Returns

Series or Index

Examples

```
>>> s = pd.Series(["String",
...                (1, 2, 3),
...                ["a", "b", "c"],
...                123,
...                -456,
...                {1: "Hello", "2": "World"}])
>>> s
0                       String
1                    (1, 2, 3)
```

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```
2                      [a, b, c]
3                            123
4                           -456
5    {1: 'Hello', '2': 'World'}
dtype: object
```

```
>>> s.str.get(1)
0        t
1        2
2        b
3      NaN
4      NaN
5    Hello
dtype: object
```

```
>>> s.str.get(-1)
0      g
1      3
2      c
3    NaN
4    NaN
5    None
dtype: object
```

pandas.Series.str.index

Series.str.**index**(*sub*, *start=0*, *end=None*)

Return lowest indexes in each string in Series/Index.

Each of the returned indexes corresponds to the position where the substring is fully contained between [start:end]. This is the same as `str.find` except instead of returning -1, it raises a ValueError when the substring is not found. Equivalent to standard `str.index`.

Parameters

sub [str] Substring being searched.

start [int] Left edge index.

end [int] Right edge index.

Returns

Series or Index of object

See also:

rindex Return highest indexes in each strings.

pandas.Series.str.join

Series.str.**join**(*sep*)

Join lists contained as elements in the Series/Index with passed delimiter.

If the elements of a Series are lists themselves, join the content of these lists using the delimiter passed to the function. This function is an equivalent to `str.join()`.

Parameters

sep [str] Delimiter to use between list entries.

Returns

Series/Index: object The list entries concatenated by intervening occurrences of the delimiter.

Raises

AttributeError If the supplied Series contains neither strings nor lists.

See also:

`str.join` Standard library version of this method.
`Series.str.split` Split strings around given separator/delimiter.

Notes

If any of the list items is not a string object, the result of the join will be *NaN*.

Examples

Example with a list that contains non-string elements.

```
>>> s = pd.Series([['lion', 'elephant', 'zebra'],
...                [1.1, 2.2, 3.3],
...                ['cat', np.nan, 'dog'],
...                ['cow', 4.5, 'goat'],
...                ['duck', ['swan', 'fish'], 'guppy']])
>>> s
0        [lion, elephant, zebra]
1                [1.1, 2.2, 3.3]
2                [cat, nan, dog]
3               [cow, 4.5, goat]
4    [duck, [swan, fish], guppy]
dtype: object
```

Join all lists using a '-'. The lists containing object(s) of types other than str will produce a NaN.

```
>>> s.str.join('-')
0    lion-elephant-zebra
1                    NaN
2                    NaN
3                    NaN
4                    NaN
dtype: object
```

pandas.Series.str.len

Series.str.**len**()

Compute the length of each element in the Series/Index.

The element may be a sequence (such as a string, tuple or list) or a collection (such as a dictionary).

Returns

Series or Index of int A Series or Index of integer values indicating the length of each element in the Series or Index.

See also:

str.len Python built-in function returning the length of an object.
Series.size Returns the length of the Series.

Examples

Returns the length (number of characters) in a string. Returns the number of entries for dictionaries, lists or tuples.

```
>>> s = pd.Series(['dog',
...                '',
...                5,
...                {'foo' : 'bar'},
...                [2, 3, 5, 7],
...                ('one', 'two', 'three')])
>>> s
0                  dog
1
2                    5
3       {'foo': 'bar'}
4         [2, 3, 5, 7]
5    (one, two, three)
dtype: object
>>> s.str.len()
0    3.0
1    0.0
2    NaN
3    1.0
4    4.0
5    3.0
dtype: float64
```

pandas.Series.str.ljust

Series.str.**ljust**(*width*, *fillchar=' '*)

Pad right side of strings in the Series/Index.

Equivalent to `str.ljust()`.

Parameters

width [int] Minimum width of resulting string; additional characters will be filled with `fillchar`.

fillchar [str] Additional character for filling, default is whitespace.

Returns

filled [Series/Index of objects.]

pandas.Series.str.lower

Series.str.**lower**()

Convert strings in the Series/Index to lowercase.

Equivalent to `str.lower()`.

Returns

Series or Index of object

See also:

Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold Removes all case distinctions in the string.

Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0                 lower
1              CAPITALS
2    this is a sentence
3              SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0                 lower
1              capitals
2    this is a sentence
3              swapcase
dtype: object
```

```
>>> s.str.upper()
0                 LOWER
1              CAPITALS
2    THIS IS A SENTENCE
3              SWAPCASE
dtype: object
```

```
>>> s.str.title()
0                 Lower
1              Capitals
2    This Is A Sentence
3              Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0                 Lower
1              Capitals
```

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```
2    This is a sentence
3              Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0                 LOWER
1              capitals
2    THIS IS A SENTENCE
3              sWaPcAsE
dtype: object
```

pandas.Series.str.lstrip

Series.str.**lstrip**(*to_strip=None*)

Remove leading characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from left side. Equivalent to `str.lstrip()`.

Parameters

to_strip [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

Returns

Series or Index of object

See also:

Series.str.strip Remove leading and trailing characters in Series/Index.
Series.str.lstrip Remove leading characters in Series/Index.
Series.str.rstrip Remove trailing characters in Series/Index.

Examples

```
>>> s = pd.Series(['1. Ant.  ', '2. Bee!\n', '3. Cat?\t', np.nan])
>>> s
0    1. Ant.
1    2. Bee!\n
2    3. Cat?\t
3          NaN
dtype: object
```

```
>>> s.str.strip()
0    1. Ant.
1    2. Bee!
2    3. Cat?
3        NaN
dtype: object
```

```
>>> s.str.lstrip('123.')
0    Ant.
1    Bee!\n
```

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```
2    Cat?\t
3       NaN
dtype: object
```

```
>>> s.str.rstrip('.!? \n\t')
0    1. Ant
1    2. Bee
2    3. Cat
3       NaN
dtype: object
```

```
>>> s.str.strip('123.!? \n\t')
0    Ant
1    Bee
2    Cat
3    NaN
dtype: object
```

pandas.Series.str.match

Series.str.**match**(*pat*, *case=True*, *flags=0*, *na=None*)

Determine if each string starts with a match of a regular expression.

Parameters

pat [str] Character sequence or regular expression.

case [bool, default True] If True, case sensitive.

flags [int, default 0 (no flags)] Regex module flags, e.g. re.IGNORECASE.

na [scalar, optional] Fill value for missing values. The default depends on dtype of the array. For object-dtype, `numpy.nan` is used. For `StringDtype`, `pandas.NA` is used.

Returns

Series/array of boolean values

See also:

fullmatch Stricter matching that requires the entire string to match.
contains Analogous, but less strict, relying on re.search instead of re.match.
extract Extract matched groups.

pandas.Series.str.normalize

Series.str.**normalize**(*form*)

Return the Unicode normal form for the strings in the Series/Index.

For more information on the forms, see the `unicodedata.normalize()`.

Parameters

form [{'NFC', 'NFKC', 'NFD', 'NFKD'}] Unicode form.

Returns

normalized [Series/Index of objects]

pandas.Series.str.pad

Series.str.**pad**(*width*, *side='left'*, *fillchar=' '*)

Pad strings in the Series/Index up to width.

Parameters

width [int] Minimum width of resulting string; additional characters will be filled with character defined in *fillchar*.

side [{'left', 'right', 'both'}, default 'left'] Side from which to fill resulting string.

fillchar [str, default ' '] Additional character for filling, default is whitespace.

Returns

Series or Index of object Returns Series or Index with minimum number of char in object.

See also:

Series.str.rjust Fills the left side of strings with an arbitrary character. Equivalent to `Series.str.pad(side='left')`.

Series.str.ljust Fills the right side of strings with an arbitrary character. Equivalent to `Series.str.pad(side='right')`.

Series.str.center Fills both sides of strings with an arbitrary character. Equivalent to `Series.str.pad(side='both')`.

Series.str.zfill Pad strings in the Series/Index by prepending '0' character. Equivalent to `Series.str.pad(side='left', fillchar='0')`.

Examples

```
>>> s = pd.Series(["caribou", "tiger"])
>>> s
0    caribou
1      tiger
dtype: object
```

```
>>> s.str.pad(width=10)
0       caribou
1         tiger
dtype: object
```

```
>>> s.str.pad(width=10, side='right', fillchar='-')
0    caribou---
1    tiger-----
dtype: object
```

```
>>> s.str.pad(width=10, side='both', fillchar='-')
0    -caribou--
1    --tiger---
dtype: object
```

pandas.Series.str.partition

Series.str.**partition**(*sep=' '*, *expand=True*)

Split the string at the first occurrence of *sep*.

This method splits the string at the first occurrence of *sep*, and returns 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing the string itself, followed by two empty strings.

Parameters

sep [str, default whitespace] String to split on.

expand [bool, default True] If True, return DataFrame/MultiIndex expanding dimensionality. If False, return Series/Index.

Returns

DataFrame/MultiIndex or Series/Index of objects

See also:

rpartition Split the string at the last occurrence of *sep*.
Series.str.split Split strings around given separators.
str.partition Standard library version.

Examples

```
>>> s = pd.Series(['Linda van der Berg', 'George Pitt-Rivers'])
>>> s
0    Linda van der Berg
1    George Pitt-Rivers
dtype: object
```

```
>>> s.str.partition()
        0  1             2
0   Linda     van der Berg
1  George      Pitt-Rivers
```

To partition by the last space instead of the first one:

```
>>> s.str.rpartition()
               0  1            2
0  Linda van der            Berg
1         George     Pitt-Rivers
```

To partition by something different than a space:

```
>>> s.str.partition('-')
                    0  1       2
0  Linda van der Berg
1         George Pitt  -  Rivers
```

To return a Series containing tuples instead of a DataFrame:

```
>>> s.str.partition('-', expand=False)
0    (Linda van der Berg, , )
1    (George Pitt, -, Rivers)
dtype: object
```

Also available on indices:

```
>>> idx = pd.Index(['X 123', 'Y 999'])
>>> idx
Index(['X 123', 'Y 999'], dtype='object')
```

Which will create a MultiIndex:

```
>>> idx.str.partition()
MultiIndex([('X', ' ', '123'),
            ('Y', ' ', '999')],
           )
```

Or an index with tuples with `expand=False`:

```
>>> idx.str.partition(expand=False)
Index([('X', ' ', '123'), ('Y', ' ', '999')], dtype='object')
```

pandas.Series.str.repeat

`Series.str.`**`repeat`**(*repeats*)

Duplicate each string in the Series or Index.

Parameters

repeats [int or sequence of int] Same value for all (int) or different value per (sequence).

Returns

Series or Index of object Series or Index of repeated string objects specified by input parameter repeats.

Examples

```
>>> s = pd.Series(['a', 'b', 'c'])
>>> s
0    a
1    b
2    c
dtype: object
```

Single int repeats string in Series

```
>>> s.str.repeat(repeats=2)
0    aa
1    bb
2    cc
dtype: object
```

Sequence of int repeats corresponding string in Series

```
>>> s.str.repeat(repeats=[1, 2, 3])
0      a
1     bb
2    ccc
dtype: object
```

pandas.Series.str.replace

Series.str.**replace**(*pat*, *repl*, *n=- 1*, *case=None*, *flags=0*, *regex=None*)

Replace each occurrence of pattern/regex in the Series/Index.

Equivalent to `str.replace()` or `re.sub()`, depending on the regex value.

Parameters

pat [str or compiled regex] String can be a character sequence or regular expression.

repl [str or callable] Replacement string or a callable. The callable is passed the regex match object and must return a replacement string to be used. See `re.sub()`.

n [int, default -1 (all)] Number of replacements to make from start.

case [bool, default None] Determines if replace is case sensitive:

- If True, case sensitive (the default if *pat* is a string)
- Set to False for case insensitive
- Cannot be set if *pat* is a compiled regex.

flags [int, default 0 (no flags)] Regex module flags, e.g. re.IGNORECASE. Cannot be set if *pat* is a compiled regex.

regex [bool, default True] Determines if assumes the passed-in pattern is a regular expression:

- If True, assumes the passed-in pattern is a regular expression.
- If False, treats the pattern as a literal string
- Cannot be set to False if *pat* is a compiled regex or *repl* is a callable.

New in version 0.23.0.

Returns

Series or Index of object A copy of the object with all matching occurrences of *pat* replaced by *repl*.

Raises

ValueError

- if *regex* is False and *repl* is a callable or *pat* is a compiled regex
- if *pat* is a compiled regex and *case* or *flags* is set

Notes

When *pat* is a compiled regex, all flags should be included in the compiled regex. Use of *case*, *flags*, or *regex=False* with a compiled regex will raise an error.

Examples

When *pat* is a string and *regex* is True (the default), the given *pat* is compiled as a regex. When *repl* is a string, it replaces matching regex patterns as with `re.sub()`. NaN value(s) in the Series are left as is:

```
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f.', 'ba', regex=True)
0    bao
1    baz
2    NaN
dtype: object
```

When *pat* is a string and *regex* is False, every *pat* is replaced with *repl* as with `str.replace()`:

```
>>> pd.Series(['f.o', 'fuz', np.nan]).str.replace('f.', 'ba', regex=False)
0    bao
1    fuz
2    NaN
dtype: object
```

When *repl* is a callable, it is called on every *pat* using `re.sub()`. The callable should expect one positional argument (a regex object) and return a string.

To get the idea:

```
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f', repr)
0    <re.Match object; span=(0, 1), match='f'>oo
1    <re.Match object; span=(0, 1), match='f'>uz
2                                            NaN
dtype: object
```

Reverse every lowercase alphabetic word:

```
>>> repl = lambda m: m.group(0)[::-1]
>>> pd.Series(['foo 123', 'bar baz', np.nan]).str.replace(r'[a-z]+', repl)
0    oof 123
1    rab zab
2        NaN
dtype: object
```

Using regex groups (extract second group and swap case):

```
>>> pat = r"(?P<one>\w+) (?P<two>\w+) (?P<three>\w+)"
>>> repl = lambda m: m.group('two').swapcase()
>>> pd.Series(['One Two Three', 'Foo Bar Baz']).str.replace(pat, repl)
0    tWO
1    bAR
dtype: object
```

Using a compiled regex with flags

```
>>> import re
>>> regex_pat = re.compile(r'FUZ', flags=re.IGNORECASE)
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace(regex_pat, 'bar')
0    foo
1    bar
2    NaN
dtype: object
```

pandas.Series.str.rfind

Series.str.**rfind**(*sub*, *start=0*, *end=None*)

Return highest indexes in each strings in the Series/Index.

Each of returned indexes corresponds to the position where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.rfind()`.

Parameters

sub [str] Substring being searched.

start [int] Left edge index.

end [int] Right edge index.

Returns

Series or Index of int.

See also:

find Return lowest indexes in each strings.

pandas.Series.str.rindex

Series.str.**rindex**(*sub*, *start=0*, *end=None*)

Return highest indexes in each string in Series/Index.

Each of the returned indexes corresponds to the position where the substring is fully contained between [start:end]. This is the same as `str.rfind` except instead of returning -1, it raises a ValueError when the substring is not found. Equivalent to standard `str.rindex`.

Parameters

sub [str] Substring being searched.

start [int] Left edge index.

end [int] Right edge index.

Returns

Series or Index of object

See also:

index Return lowest indexes in each strings.

pandas.Series.str.rjust

Series.str.**rjust**(*width*, *fillchar=' '*)

Pad left side of strings in the Series/Index.

Equivalent to `str.rjust()`.

Parameters

width [int] Minimum width of resulting string; additional characters will be filled with `fillchar`.

fillchar [str] Additional character for filling, default is whitespace.

Returns

filled [Series/Index of objects.]

pandas.Series.str.rpartition

Series.str.**rpartition**(*sep=' '*, *expand=True*)

Split the string at the last occurrence of *sep*.

This method splits the string at the last occurrence of *sep*, and returns 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing two empty strings, followed by the string itself.

Parameters

sep [str, default whitespace] String to split on.

expand [bool, default True] If True, return DataFrame/MultiIndex expanding dimensionality. If False, return Series/Index.

Returns

DataFrame/MultiIndex or Series/Index of objects

See also:

partition Split the string at the first occurrence of *sep*.
Series.str.split Split strings around given separators.
str.partition Standard library version.

Examples

```
>>> s = pd.Series(['Linda van der Berg', 'George Pitt-Rivers'])
>>> s
0    Linda van der Berg
1    George Pitt-Rivers
dtype: object
```

```
>>> s.str.partition()
        0  1             2
0   Linda     van der Berg
1  George      Pitt-Rivers
```

To partition by the last space instead of the first one:

```
>>> s.str.rpartition()
               0  1            2
0  Linda van der            Berg
1         George     Pitt-Rivers
```

To partition by something different than a space:

```
>>> s.str.partition('-')
                    0  1       2
0  Linda van der Berg
1         George Pitt  -  Rivers
```

To return a Series containing tuples instead of a DataFrame:

```
>>> s.str.partition('-', expand=False)
0    (Linda van der Berg, , )
1    (George Pitt, -, Rivers)
dtype: object
```

Also available on indices:

```
>>> idx = pd.Index(['X 123', 'Y 999'])
>>> idx
Index(['X 123', 'Y 999'], dtype='object')
```

Which will create a MultiIndex:

```
>>> idx.str.partition()
MultiIndex([('X', ' ', '123'),
            ('Y', ' ', '999')],
           )
```

Or an index with tuples with `expand=False`:

```
>>> idx.str.partition(expand=False)
Index([('X', ' ', '123'), ('Y', ' ', '999')], dtype='object')
```

pandas.Series.str.rstrip

`Series.str.`**`rstrip`**(*to_strip=None*)

Remove trailing characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from right side. Equivalent to `str.rstrip()`.

Parameters

to_strip [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

Returns

Series or Index of object

See also:

Series.str.strip Remove leading and trailing characters in Series/Index.
Series.str.lstrip Remove leading characters in Series/Index.
Series.str.rstrip Remove trailing characters in Series/Index.

Examples

```
>>> s = pd.Series(['1. Ant.  ', '2. Bee!\n', '3. Cat?\t', np.nan])
>>> s
0    1. Ant.
1    2. Bee!\n
2    3. Cat?\t
3          NaN
dtype: object
```

```
>>> s.str.strip()
0    1. Ant.
1    2. Bee!
2    3. Cat?
3        NaN
dtype: object
```

```
>>> s.str.lstrip('123.')
0    Ant.
1    Bee!\n
2    Cat?\t
3       NaN
dtype: object
```

```
>>> s.str.rstrip('.!? \n\t')
0    1. Ant
1    2. Bee
2    3. Cat
3       NaN
dtype: object
```

```
>>> s.str.strip('123.!? \n\t')
0    Ant
1    Bee
2    Cat
3    NaN
dtype: object
```

pandas.Series.str.slice

Series.str.**slice**(*start=None*, *stop=None*, *step=None*)

Slice substrings from each element in the Series or Index.

Parameters

start [int, optional] Start position for slice operation.

stop [int, optional] Stop position for slice operation.

step [int, optional] Step size for slice operation.

Returns

Series or Index of object Series or Index from sliced substring from original string object.

See also:

Series.str.slice_replace Replace a slice with a string.

Series.str.get Return element at position. Equivalent to *Series.str.slice(start=i, stop=i+1)* with *i* being the position.

Examples

```
>>> s = pd.Series(["koala", "fox", "chameleon"])
>>> s
0        koala
1          fox
2    chameleon
dtype: object
```

```
>>> s.str.slice(start=1)
0        oala
1          ox
```

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```
2    hameleon
dtype: object
```

```
>>> s.str.slice(start=-1)
0           a
1           x
2           n
dtype: object
```

```
>>> s.str.slice(stop=2)
0    ko
1    fo
2    ch
dtype: object
```

```
>>> s.str.slice(step=2)
0      kaa
1       fx
2    caeen
dtype: object
```

```
>>> s.str.slice(start=0, stop=5, step=3)
0    kl
1     f
2    cm
dtype: object
```

Equivalent behaviour to:

```
>>> s.str[0:5:3]
0    kl
1     f
2    cm
dtype: object
```

pandas.Series.str.slice_replace

Series.str.**slice_replace**(*start=None*, *stop=None*, *repl=None*)

Replace a positional slice of a string with another value.

Parameters

start [int, optional] Left index position to use for the slice. If not specified (None), the slice is unbounded on the left, i.e. slice from the start of the string.

stop [int, optional] Right index position to use for the slice. If not specified (None), the slice is unbounded on the right, i.e. slice until the end of the string.

repl [str, optional] String for replacement. If not specified (None), the sliced region is replaced with an empty string.

Returns

Series or Index Same type as the original object.

See also:

Series.str.slice Just slicing without replacement.

Examples

```
>>> s = pd.Series(['a', 'ab', 'abc', 'abdc', 'abcde'])
>>> s
0        a
1       ab
2      abc
3     abdc
4    abcde
dtype: object
```

Specify just *start*, meaning replace *start* until the end of the string with *repl*.

```
>>> s.str.slice_replace(1, repl='X')
0    aX
1    aX
2    aX
3    aX
4    aX
dtype: object
```

Specify just *stop*, meaning the start of the string to *stop* is replaced with *repl*, and the rest of the string is included.

```
>>> s.str.slice_replace(stop=2, repl='X')
0       X
1       X
2      Xc
3     Xdc
4    Xcde
dtype: object
```

Specify *start* and *stop*, meaning the slice from *start* to *stop* is replaced with *repl*. Everything before or after *start* and *stop* is included as is.

```
>>> s.str.slice_replace(start=1, stop=3, repl='X')
0      aX
1      aX
2      aX
3     aXc
4    aXde
dtype: object
```

pandas.Series.str.split

`Series.str.`**`split`**(*pat=None*, *n=- 1*, *expand=False*)

Split strings around given separator/delimiter.

Splits the string in the Series/Index from the beginning, at the specified delimiter string. Equivalent to `str.split()`.

Parameters

pat [str, optional] String or regular expression to split on. If not specified, split on whitespace.

n [int, default -1 (all)] Limit number of splits in output. `None`, 0 and -1 will be interpreted as return all splits.

expand [bool, default False] Expand the split strings into separate columns.

- If `True`, return DataFrame/MultiIndex expanding dimensionality.
- If `False`, return Series/Index, containing lists of strings.

Returns

Series, Index, DataFrame or MultiIndex Type matches caller unless `expand=True` (see Notes).

See also:

Series.str.split Split strings around given separator/delimiter.
Series.str.rsplit Splits string around given separator/delimiter, starting from the right.
Series.str.join Join lists contained as elements in the Series/Index with passed delimiter.
str.split Standard library version for split.
str.rsplit Standard library version for rsplit.

Notes

The handling of the *n* keyword depends on the number of found splits:

- If found splits > *n*, make first *n* splits only
- If found splits <= *n*, make all splits
- If for a certain row the number of found splits < *n*, append *None* for padding up to *n* if `expand=True`

If using `expand=True`, Series and Index callers return DataFrame and MultiIndex objects, respectively.

Examples

```
>>> s = pd.Series(
...     [
...         "this is a regular sentence",
...         "https://docs.python.org/3/tutorial/index.html",
...         np.nan
...     ]
... )
>>> s
0                       this is a regular sentence
1    https://docs.python.org/3/tutorial/index.html
2                                              NaN
dtype: object
```

In the default setting, the string is split by whitespace.

```
>>> s.str.split()
0                   [this, is, a, regular, sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

Without the *n* parameter, the outputs of *rsplit* and *split* are identical.

```
>>> s.str.rsplit()
0                   [this, is, a, regular, sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

The *n* parameter can be used to limit the number of splits on the delimiter. The outputs of *split* and *rsplit* are different.

```
>>> s.str.split(n=2)
0                     [this, is, a regular sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

```
>>> s.str.rsplit(n=2)
0                     [this is a, regular, sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

The *pat* parameter can be used to split by other characters.

```
>>> s.str.split(pat="/")
0                         [this is a regular sentence]
1    [https:, , docs.python.org, 3, tutorial, index...
2                                                  NaN
dtype: object
```

When using `expand=True`, the split elements will expand out into separate columns. If NaN is present, it is propagated throughout the columns during the split.

```
>>> s.str.split(expand=True)
                                               0     1     2        3         4
0                                           this    is     a  regular  sentence
1  https://docs.python.org/3/tutorial/index.html  None  None     None      None
2                                            NaN   NaN   NaN      NaN       NaN
```

For slightly more complex use cases like splitting the html document name from a url, a combination of parameter settings can be used.

```
>>> s.str.rsplit("/", n=1, expand=True)
                                    0           1
0          this is a regular sentence        None
1  https://docs.python.org/3/tutorial  index.html
2                                 NaN         NaN
```

Remember to escape special characters when explicitly using regular expressions.

```
>>> s = pd.Series(["1+1=2"])
>>> s
0    1+1=2
dtype: object
>>> s.str.split(r"\+|=", expand=True)
     0    1    2
0    1    1    2
```

pandas.Series.str.rsplit

Series.str.**rsplit**(*pat=None*, *n=- 1*, *expand=False*)

Split strings around given separator/delimiter.

Splits the string in the Series/Index from the end, at the specified delimiter string. Equivalent to `str.rsplit()`.

Parameters

pat [str, optional] String or regular expression to split on. If not specified, split on whitespace.

n [int, default -1 (all)] Limit number of splits in output. `None`, 0 and -1 will be interpreted as return all splits.

expand [bool, default False] Expand the split strings into separate columns.

- If `True`, return DataFrame/MultiIndex expanding dimensionality.
- If `False`, return Series/Index, containing lists of strings.

Returns

Series, Index, DataFrame or MultiIndex Type matches caller unless `expand=True` (see Notes).

See also:

Series.str.split Split strings around given separator/delimiter.
Series.str.rsplit Splits string around given separator/delimiter, starting from the right.
Series.str.join Join lists contained as elements in the Series/Index with passed delimiter.
str.split Standard library version for split.
str.rsplit Standard library version for rsplit.

Notes

The handling of the *n* keyword depends on the number of found splits:

- If found splits > *n*, make first *n* splits only
- If found splits <= *n*, make all splits
- If for a certain row the number of found splits < *n*, append *None* for padding up to *n* if `expand=True`

If using `expand=True`, Series and Index callers return DataFrame and MultiIndex objects, respectively.

Examples

```
>>> s = pd.Series(
...     [
...         "this is a regular sentence",
...         "https://docs.python.org/3/tutorial/index.html",
...         np.nan
...     ]
... )
>>> s
0                    this is a regular sentence
1    https://docs.python.org/3/tutorial/index.html
2                                            NaN
dtype: object
```

In the default setting, the string is split by whitespace.

```
>>> s.str.split()
0                   [this, is, a, regular, sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

Without the *n* parameter, the outputs of *rsplit* and *split* are identical.

```
>>> s.str.rsplit()
0                   [this, is, a, regular, sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

The *n* parameter can be used to limit the number of splits on the delimiter. The outputs of *split* and *rsplit* are different.

```
>>> s.str.split(n=2)
0                     [this, is, a regular sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

```
>>> s.str.rsplit(n=2)
0                     [this is a, regular, sentence]
1    [https://docs.python.org/3/tutorial/index.html]
2                                                NaN
dtype: object
```

The *pat* parameter can be used to split by other characters.

```
>>> s.str.split(pat="/")
0                         [this is a regular sentence]
1    [https:, , docs.python.org, 3, tutorial, index...
2                                                  NaN
dtype: object
```

When using `expand=True`, the split elements will expand out into separate columns. If NaN is present, it is propagated throughout the columns during the split.

```
>>> s.str.split(expand=True)
                                               0     1     2        3         4
0                                           this    is     a  regular  sentence
1  https://docs.python.org/3/tutorial/index.html  None  None     None      None
2                                            NaN   NaN   NaN      NaN       NaN
```

For slightly more complex use cases like splitting the html document name from a url, a combination of parameter settings can be used.

```
>>> s.str.rsplit("/", n=1, expand=True)
                                    0           1
0          this is a regular sentence        None
1  https://docs.python.org/3/tutorial  index.html
2                                 NaN         NaN
```

Remember to escape special characters when explicitly using regular expressions.

```
>>> s = pd.Series(["1+1=2"])
>>> s
0    1+1=2
dtype: object
>>> s.str.split(r"\+|=", expand=True)
     0    1    2
0    1    1    2
```

pandas.Series.str.startswith

Series.str.**startswith**(*pat*, *na=None*)

Test if the start of each string element matches a pattern.

Equivalent to `str.startswith()`.

Parameters

pat [str] Character sequence. Regular expressions are not accepted.

na [object, default NaN] Object shown if element tested is not a string. The default depends on dtype of the array. For object-dtype, `numpy.nan` is used. For `StringDtype`, `pandas.NA` is used.

Returns

Series or Index of bool A Series of booleans indicating whether the given pattern matches the start of each string element.

See also:

`str.startswith` Python standard library string method.
`Series.str.endswith` Same as startswith, but tests the end of string.
`Series.str.contains` Tests if string element contains a pattern.

Examples

```
>>> s = pd.Series(['bat', 'Bear', 'cat', np.nan])
>>> s
0     bat
1    Bear
2     cat
3     NaN
dtype: object
```

```
>>> s.str.startswith('b')
0     True
1    False
2    False
3      NaN
dtype: object
```

Specifying *na* to be *False* instead of *NaN*.

```
>>> s.str.startswith('b', na=False)
0     True
1    False
2    False
```

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```
3    False
dtype: bool
```

pandas.Series.str.strip

Series.str.**strip**(*to_strip=None*)

Remove leading and trailing characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from left and right sides. Equivalent to `str.strip()`.

Parameters

to_strip [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

Returns

Series or Index of object

See also:

Series.str.strip Remove leading and trailing characters in Series/Index.
Series.str.lstrip Remove leading characters in Series/Index.
Series.str.rstrip Remove trailing characters in Series/Index.

Examples

```
>>> s = pd.Series(['1. Ant.  ', '2. Bee!\n', '3. Cat?\t', np.nan])
>>> s
0    1. Ant.
1    2. Bee!\n
2    3. Cat?\t
3          NaN
dtype: object
```

```
>>> s.str.strip()
0    1. Ant.
1    2. Bee!
2    3. Cat?
3        NaN
dtype: object
```

```
>>> s.str.lstrip('123.')
0    Ant.
1    Bee!\n
2    Cat?\t
3       NaN
dtype: object
```

```
>>> s.str.rstrip('.!? \n\t')
0    1. Ant
1    2. Bee
2    3. Cat
```

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```
3       NaN
dtype: object
```

```
>>> s.str.strip('123.!? \n\t')
0    Ant
1    Bee
2    Cat
3    NaN
dtype: object
```

pandas.Series.str.swapcase

Series.str.**swapcase**()

Convert strings in the Series/Index to be swapcased.

Equivalent to `str.swapcase()`.

Returns

Series or Index of object

See also:

Series.str.lower	Converts all characters to lowercase.
Series.str.upper	Converts all characters to uppercase.
Series.str.title	Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize	Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase	Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold	Removes all case distinctions in the string.

Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0                 lower
1              CAPITALS
2    this is a sentence
3              SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0                 lower
1              capitals
2    this is a sentence
3              swapcase
dtype: object
```

```
>>> s.str.upper()
0                 LOWER
1              CAPITALS
2    THIS IS A SENTENCE
3              SWAPCASE
dtype: object
```

```
>>> s.str.title()
0                 Lower
1              Capitals
2    This Is A Sentence
3              Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0                 Lower
1              Capitals
2    This is a sentence
3              Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0                 LOWER
1              capitals
2    THIS IS A SENTENCE
3              sWaPcAsE
dtype: object
```

pandas.Series.str.title

Series.str.**title**()

Convert strings in the Series/Index to titlecase.

Equivalent to `str.title()`.

Returns

Series or Index of object

See also:

Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold Removes all case distinctions in the string.

Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0                 lower
1              CAPITALS
2    this is a sentence
3              SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0                 lower
1              capitals
2    this is a sentence
```

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```
3              swapcase
dtype: object
```

```
>>> s.str.upper()
0                 LOWER
1              CAPITALS
2    THIS IS A SENTENCE
3              SWAPCASE
dtype: object
```

```
>>> s.str.title()
0                 Lower
1              Capitals
2    This Is A Sentence
3              Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0                 Lower
1              Capitals
2    This is a sentence
3              Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0                 LOWER
1              capitals
2    THIS IS A SENTENCE
3              sWaPcAsE
dtype: object
```

pandas.Series.str.translate

Series.str.**translate**(*table*)

Map all characters in the string through the given mapping table.

Equivalent to standard `str.translate()`.

Parameters

table [dict] Table is a mapping of Unicode ordinals to Unicode ordinals, strings, or None. Unmapped characters are left untouched. Characters mapped to None are deleted. `str.maketrans()` is a helper function for making translation tables.

Returns

Series or Index

pandas.Series.str.upper

Series.str.**upper**()

Convert strings in the Series/Index to uppercase.

Equivalent to `str.upper()`.

Returns

Series or Index of object

See also:

Series.str.lower	Converts all characters to lowercase.
Series.str.upper	Converts all characters to uppercase.
Series.str.title	Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize	Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase	Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold	Removes all case distinctions in the string.

Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0                 lower
1              CAPITALS
2    this is a sentence
3              SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0                 lower
1              capitals
2    this is a sentence
3              swapcase
dtype: object
```

```
>>> s.str.upper()
0                 LOWER
1              CAPITALS
2    THIS IS A SENTENCE
3              SWAPCASE
dtype: object
```

```
>>> s.str.title()
0                 Lower
1              Capitals
2    This Is A Sentence
3              Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0                 Lower
1              Capitals
2    This is a sentence
3              Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0                 LOWER
1              capitals
2    THIS IS A SENTENCE
3              sWaPcAsE
dtype: object
```

pandas.Series.str.wrap

Series.str.**wrap**(*width*, ***kwargs*)

Wrap strings in Series/Index at specified line width.

This method has the same keyword parameters and defaults as `textwrap.TextWrapper`.

Parameters

width [int] Maximum line width.

expand_tabs [bool, optional] If True, tab characters will be expanded to spaces (default: True).

replace_whitespace [bool, optional] If True, each whitespace character (as defined by string.whitespace) remaining after tab expansion will be replaced by a single space (default: True).

drop_whitespace [bool, optional] If True, whitespace that, after wrapping, happens to end up at the beginning or end of a line is dropped (default: True).

break_long_words [bool, optional] If True, then words longer than width will be broken in order to ensure that no lines are longer than width. If it is false, long words will not be broken, and some lines may be longer than width (default: True).

break_on_hyphens [bool, optional] If True, wrapping will occur preferably on whitespace and right after hyphens in compound words, as it is customary in English. If false, only whitespaces will be considered as potentially good places for line breaks, but you need to set break_long_words to false if you want truly insecable words (default: True).

Returns

Series or Index

Notes

Internally, this method uses a `textwrap.TextWrapper` instance with default settings. To achieve behavior matching R's stringr library str_wrap function, use the arguments:

- expand_tabs = False
- replace_whitespace = True
- drop_whitespace = True
- break_long_words = False
- break_on_hyphens = False

Examples

```
>>> s = pd.Series(['line to be wrapped', 'another line to be wrapped'])
>>> s.str.wrap(12)
0             line to be\nwrapped
1    another line\nto be\nwrapped
dtype: object
```

pandas.Series.str.zfill

Series.str.**zfill**(*width*)

Pad strings in the Series/Index by prepending '0' characters.

Strings in the Series/Index are padded with '0' characters on the left of the string to reach a total string length *width*. Strings in the Series/Index with length greater or equal to *width* are unchanged.

Parameters

width [int] Minimum length of resulting string; strings with length less than *width* be prepended with '0' characters.

Returns

Series/Index of objects.

See also:

Series.str.rjust Fills the left side of strings with an arbitrary character.
Series.str.ljust Fills the right side of strings with an arbitrary character.
Series.str.pad Fills the specified sides of strings with an arbitrary character.
Series.str.center Fills both sides of strings with an arbitrary character.

Notes

Differs from `str.zfill()` which has special handling for '+'/'-' in the string.

Examples

```
>>> s = pd.Series(['-1', '1', '1000', 10, np.nan])
>>> s
0      -1
1       1
2    1000
3      10
4     NaN
dtype: object
```

Note that `10` and `NaN` are not strings, therefore they are converted to `NaN`. The minus sign in `'-1'` is treated as a regular character and the zero is added to the left of it (`str.zfill()` would have moved it to the left). `1000` remains unchanged as it is longer than *width*.

```
>>> s.str.zfill(3)
0     0-1
1     001
2    1000
3     NaN
```

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```
4     NaN
dtype: object
```

pandas.Series.str.isalnum

Series.str.**isalnum**()

Check whether all characters in each string are alphanumeric.

This is equivalent to running the Python string method `str.isalnum()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.isalpha

`Series.str.`**`isalpha`**`()`

Check whether all characters in each string are alphabetic.

This is equivalent to running the Python string method `str.isalpha()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
```

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```
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.isdigit

Series.str.**isdigit**()

Check whether all characters in each string are digits.

This is equivalent to running the Python string method `str.isdigit()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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```
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.isspace

Series.str.**isspace**()

Check whether all characters in each string are alphanumeric.

This is equivalent to running the Python string method `str.isalnum()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
```

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```
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.islower

Series.str.**islower**()

Check whether all characters in each string are lowercase.

This is equivalent to running the Python string method `str.islower()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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```
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.isupper

`Series.str.`**`isupper`**`()`

Check whether all characters in each string are uppercase.

This is equivalent to running the Python string method `str.isupper()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
```

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```
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.istitle

Series.str.**istitle**()

Check whether all characters in each string are titlecase.

This is equivalent to running the Python string method `str.istitle()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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```
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.isnumeric

Series.str.**isnumeric**()

Check whether all characters in each string are numeric.

This is equivalent to running the Python string method `str.isnumeric()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
```

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```
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.isdecimal

Series.str.**isdecimal**()

Check whether all characters in each string are decimal.

This is equivalent to running the Python string method `str.isdecimal()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0     True
1    False
2    False
3    False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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```
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2     True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

pandas.Series.str.get_dummies

Series.str.**get_dummies**(*sep='|'*)

Return DataFrame of dummy/indicator variables for Series.

Each string in Series is split by sep and returned as a DataFrame of dummy/indicator variables.

Parameters

sep [str, default "|"] String to split on.

Returns

DataFrame Dummy variables corresponding to values of the Series.

See also:

get_dummies Convert categorical variable into dummy/indicator variables.

Examples

```
>>> pd.Series(['a|b', 'a', 'a|c']).str.get_dummies()
a  b  c
0  1  1  0
1  1  0  0
2  1  0  1
```

```
>>> pd.Series(['a|b', np.nan, 'a|c']).str.get_dummies()
a  b  c
0  1  1  0
1  0  0  0
2  1  0  1
```

Categorical accessor

Categorical-dtype specific methods and attributes are available under the `Series.cat` accessor.

Series.cat.categories	The categories of this categorical.
Series.cat.ordered	Whether the categories have an ordered relationship.
Series.cat.codes	Return Series of codes as well as the index.

pandas.Series.cat.categories

`Series.cat.`**`categories`**

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to *categories* is a inplace operation!

Raises

ValueError If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

See also:

rename_categories	Rename categories.
reorder_categories	Reorder categories.
add_categories	Add new categories.
remove_categories	Remove the specified categories.
remove_unused_categories	Remove categories which are not used.
set_categories	Set the categories to the specified ones.

pandas.Series.cat.ordered

`Series.cat.`**`ordered`**

Whether the categories have an ordered relationship.

pandas.Series.cat.codes

`Series.cat.`**`codes`**

Return Series of codes as well as the index.

Series.cat.rename_categories(*args, **kwargs)	Rename categories.
Series.cat.reorder_categories(*args, **kwargs)	Reorder categories as specified in new_categories.
Series.cat.add_categories(*args, **kwargs)	Add new categories.
Series.cat.remove_categories(*args, **kwargs)	Remove the specified categories.
Series.cat.remove_unused_categories(*args, ...)	Remove categories which are not used.

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Series.cat.set_categories(*args, **kwargs)	Set the categories to the specified new_categories.
Series.cat.as_ordered(*args, **kwargs)	Set the Categorical to be ordered.
Series.cat.as_unordered(*args, **kwargs)	Set the Categorical to be unordered.

pandas.Series.cat.rename_categories

Series.cat.**rename_categories**(**args*, ***kwargs*)

Rename categories.

Parameters

new_categories [list-like, dict-like or callable] New categories which will replace old categories.

- list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
- dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.
- callable : a callable that is called on all items in the old categories and whose return values comprise the new categories.

inplace [bool, default False] Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns

cat [Categorical or None] Categorical with removed categories or None if `inplace=True`.

Raises

ValueError If new categories are list-like and do not have the same number of items than the current categories or do not validate as categories

See also:

reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

Examples

```
>>> c = pd.Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]
```

For dict-like `new_categories`, extra keys are ignored and categories not in the dictionary are passed through

```
>>> c.rename_categories({'a': 'A', 'c': 'C'})
['A', 'A', 'b']
Categories (2, object): ['A', 'b']
```

You may also provide a callable to create the new categories

```
>>> c.rename_categories(lambda x: x.upper())
['A', 'A', 'B']
Categories (2, object): ['A', 'B']
```

pandas.Series.cat.reorder_categories

Series.cat.**reorder_categories**(**args*, ***kwargs*)

Reorder categories as specified in new_categories.

new_categories need to include all old categories and no new category items.

Parameters

new_categories [Index-like] The categories in new order.

ordered [bool, optional] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace [bool, default False] Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns

cat [Categorical or None] Categorical with removed categories or None if `inplace=True`.

Raises

ValueError If the new categories do not contain all old category items or any new ones

See also:

rename_categories Rename categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

pandas.Series.cat.add_categories

Series.cat.**add_categories**(**args*, ***kwargs*)

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

Parameters

new_categories [category or list-like of category] The new categories to be included.

inplace [bool, default False] Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns

cat [Categorical or None] Categorical with new categories added or None if `inplace=True`.

Raises

ValueError If the new categories include old categories or do not validate as categories

See also:

rename_categories Rename categories.

reorder_categories Reorder categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

pandas.Series.cat.remove_categories

Series.cat.**remove_categories**(**args*, ***kwargs*)
Remove the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters

removals [category or list of categories] The categories which should be removed.

inplace [bool, default False] Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns

cat [Categorical or None] Categorical with removed categories or None if `inplace=True`.

Raises

ValueError If the removals are not contained in the categories

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

pandas.Series.cat.remove_unused_categories

Series.cat.**remove_unused_categories**(**args*, ***kwargs*)
Remove categories which are not used.

Parameters

inplace [bool, default False] Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Deprecated since version 1.2.0.

Returns

cat [Categorical or None] Categorical with unused categories dropped or None if `inplace=True`.

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
set_categories Set the categories to the specified ones.

pandas.Series.cat.set_categories

Series.cat.**set_categories**(**args*, ***kwargs*)

Set the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes, which does not considers a S1 string equal to a single char python string.

Parameters

new_categories [Index-like] The categories in new order.

ordered [bool, default False] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename [bool, default False] Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace [bool, default False] Whether or not to reorder the categories in-place or return a copy of this categorical with reordered categories.

Returns

Categorical with reordered categories or None if inplace.

Raises

ValueError If new_categories does not validate as categories

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.

pandas.Series.cat.as_ordered

Series.cat.**as_ordered**(**args*, ***kwargs*)

Set the Categorical to be ordered.

Parameters

inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to True.

Returns

Categorical or None Ordered Categorical or None if `inplace=True`.

pandas.Series.cat.as_unordered

Series.cat.**as_unordered**(**args*, ***kwargs*)

Set the Categorical to be unordered.

Parameters

inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to False.

Returns

Categorical or None Unordered Categorical or None if `inplace=True`.

Sparse accessor

Sparse-dtype specific methods and attributes are provided under the `Series.sparse` accessor.

Series.sparse.npoints	The number of non- `fill_value` points.
Series.sparse.density	The percent of non- `fill_value` points, as decimal.
Series.sparse.fill_value	Elements in *data* that are *fill_value* are not stored.
Series.sparse.sp_values	An ndarray containing the non- `fill_value` values.

pandas.Series.sparse.npoints

Series.sparse.**npoints**

The number of non- `fill_value` points.

Examples

```
>>> s = SparseArray([0, 0, 1, 1, 1], fill_value=0)
>>> s.npoints
3
```

pandas.Series.sparse.density

Series.sparse.**density**

The percent of non- `fill_value` points, as decimal.

Examples

```
>>> s = SparseArray([0, 0, 1, 1, 1], fill_value=0)
>>> s.density
0.6
```

pandas.Series.sparse.fill_value

Series.sparse.**fill_value**
Elements in *data* that are *fill_value* are not stored.

For memory savings, this should be the most common value in the array.

pandas.Series.sparse.sp_values

Series.sparse.**sp_values**
An ndarray containing the non- `fill_value` values.

Examples

```
>>> s = SparseArray([0, 0, 1, 0, 2], fill_value=0)
>>> s.sp_values
array([1, 2])
```

Series.sparse.from_coo(A[, dense_index])	Create a Series with sparse values from a scipy.sparse.coo_matrix.
Series.sparse.to_coo([row_levels, ...])	Create a scipy.sparse.coo_matrix from a Series with MultiIndex.

pandas.Series.sparse.from_coo

classmethod Series.sparse.**from_coo**(*A*, *dense_index=False*)
Create a Series with sparse values from a scipy.sparse.coo_matrix.

Parameters

A [scipy.sparse.coo_matrix]

dense_index [bool, default False] If False (default), the SparseSeries index consists of only the coords of the non-null entries of the original coo_matrix. If True, the SparseSeries index consists of the full sorted (row, col) coordinates of the coo_matrix.

Returns

s [Series] A Series with sparse values.

Examples

```
>>> from scipy import sparse
```

```
>>> A = sparse.coo_matrix(
...      ([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])), shape=(3, 4)
... )
>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'
with 3 stored elements in COOrdinate format>
```

```
>>> A.todense()
matrix([[0., 0., 1., 2.],
[3., 0., 0., 0.],
[0., 0., 0., 0.]])
```

```
>>> ss = pd.Series.sparse.from_coo(A)
>>> ss
0  2    1.0
   3    2.0
1  0    3.0
dtype: Sparse[float64, nan]
```

pandas.Series.sparse.to_coo

`Series.sparse.to_coo`(*row_levels=(0)*, *column_levels=(1)*, *sort_labels=False*)

Create a scipy.sparse.coo_matrix from a Series with MultiIndex.

Use row_levels and column_levels to determine the row and column coordinates respectively. row_levels and column_levels are the names (labels) or numbers of the levels. {row_levels, column_levels} must be a partition of the MultiIndex level names (or numbers).

Parameters

row_levels [tuple/list]

column_levels [tuple/list]

sort_labels [bool, default False] Sort the row and column labels before forming the sparse matrix.

Returns

y [scipy.sparse.coo_matrix]

rows [list (row labels)]

columns [list (column labels)]

Examples

```
>>> s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
>>> s.index = pd.MultiIndex.from_tuples(
...     [
...         (1, 2, "a", 0),
...         (1, 2, "a", 1),
...         (1, 1, "b", 0),
...         (1, 1, "b", 1),
...         (2, 1, "b", 0),
...         (2, 1, "b", 1)
...     ],
...     names=["A", "B", "C", "D"],
... )
>>> s
A  B  C  D
1  2  a  0    3.0
          1    NaN
   1  b  0    1.0
```

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```
         1    3.0
2  1  b  0    NaN
         1    NaN
dtype: float64
```

```
>>> ss = s.astype("Sparse")
>>> ss
A  B  C  D
1  2  a  0    3.0
         1    NaN
   1  b  0    1.0
         1    3.0
2  1  b  0    NaN
         1    NaN
dtype: Sparse[float64, nan]
```

```
>>> A, rows, columns = ss.sparse.to_coo(
...     row_levels=["A", "B"], column_levels=["C", "D"], sort_labels=True
... )
>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'
with 3 stored elements in COOrdinate format>
>>> A.todense()
matrix([[0., 0., 1., 3.],
[3., 0., 0., 0.],
[0., 0., 0., 0.]])
```

```
>>> rows
[(1, 1), (1, 2), (2, 1)]
>>> columns
[('a', 0), ('a', 1), ('b', 0), ('b', 1)]
```

Flags

Flags refer to attributes of the pandas object. Properties of the dataset (like the date is was recorded, the URL it was accessed from, etc.) should be stored in *Series.attrs*.

Flags(obj, *, allows_duplicate_labels)	Flags that apply to pandas objects.

pandas.Flags

class pandas.**Flags**(*obj*, *, *allows_duplicate_labels*)

Flags that apply to pandas objects.

New in version 1.2.0.

Parameters

obj [Series or DataFrame] The object these flags are associated with.

allows_duplicate_labels [bool, default True] Whether to allow duplicate labels in this object. By default, duplicate labels are permitted. Setting this to `False` will cause an *errors.DuplicateLabelError* to be raised when *index* (or columns for

DataFrame) is not unique, or any subsequent operation on introduces duplicates. See *Disallowing Duplicate Labels* for more.

> **Warning:** This is an experimental feature. Currently, many methods fail to propagate the `allows_duplicate_labels` value. In future versions it is expected that every method taking or returning one or more DataFrame or Series objects will propagate `allows_duplicate_labels`.

Notes

Attributes can be set in two ways

```
>>> df = pd.DataFrame()
>>> df.flags
<Flags(allows_duplicate_labels=True)>
>>> df.flags.allows_duplicate_labels = False
>>> df.flags
<Flags(allows_duplicate_labels=False)>
```

```
>>> df.flags['allows_duplicate_labels'] = True
>>> df.flags
<Flags(allows_duplicate_labels=True)>
```

Attributes

allows_duplicate_labels	Whether this object allows duplicate labels.

pandas.Flags.allows_duplicate_labels

property Flags.**allows_duplicate_labels**

Whether this object allows duplicate labels.

Setting `allows_duplicate_labels=False` ensures that the index (and columns of a DataFrame) are unique. Most methods that accept and return a Series or DataFrame will propagate the value of `allows_duplicate_labels`.

See *Duplicate Labels* for more.

See also:

DataFrame.attrs Set global metadata on this object.

DataFrame.set_flags Set global flags on this object.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2]}, index=['a', 'a'])
>>> df.allows_duplicate_labels
True
>>> df.allows_duplicate_labels = False
Traceback (most recent call last):
    ...
pandas.errors.DuplicateLabelError: Index has duplicates.
      positions
label
a        [0, 1]
```

Metadata

Series.attrs is a dictionary for storing global metadata for this Series.

Warning: `Series.attrs` is considered experimental and may change without warning.

Series.attrs	Dictionary of global attributes of this dataset.

3.3.14 Plotting

`Series.plot` is both a callable method and a namespace attribute for specific plotting methods of the form `Series.plot.<kind>`.

Series.plot([kind, ax, figsize, ...])	Series plotting accessor and method

Series.plot.area([x, y])	Draw a stacked area plot.
Series.plot.bar([x, y])	Vertical bar plot.
Series.plot.barh([x, y])	Make a horizontal bar plot.
Series.plot.box([by])	Make a box plot of the DataFrame columns.
Series.plot.density([bw_method, ind])	Generate Kernel Density Estimate plot using Gaussian kernels.
Series.plot.hist([by, bins])	Draw one histogram of the DataFrame's columns.
Series.plot.kde([bw_method, ind])	Generate Kernel Density Estimate plot using Gaussian kernels.
Series.plot.line([x, y])	Plot Series or DataFrame as lines.
Series.plot.pie(**kwargs)	Generate a pie plot.

pandas.Series.plot.area

Series.plot.**area**(*x=None*, *y=None*, ***kwargs*)

Draw a stacked area plot.

An area plot displays quantitative data visually. This function wraps the matplotlib area function.

Parameters

x [label or position, optional] Coordinates for the X axis. By default uses the index.

y [label or position, optional] Column to plot. By default uses all columns.

stacked [bool, default True] Area plots are stacked by default. Set to False to create a unstacked plot.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or numpy.ndarray Area plot, or array of area plots if subplots is True.

See also:

DataFrame.plot Make plots of DataFrame using matplotlib / pylab.

Examples

Draw an area plot based on basic business metrics:

```
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3, 9, 10, 6],
...     'signups': [5, 5, 6, 12, 14, 13],
...     'visits': [20, 42, 28, 62, 81, 50],
... }, index=pd.date_range(start='2018/01/01', end='2018/07/01',
...                        freq='M'))
>>> ax = df.plot.area()
```

Area plots are stacked by default. To produce an unstacked plot, pass `stacked=False`:

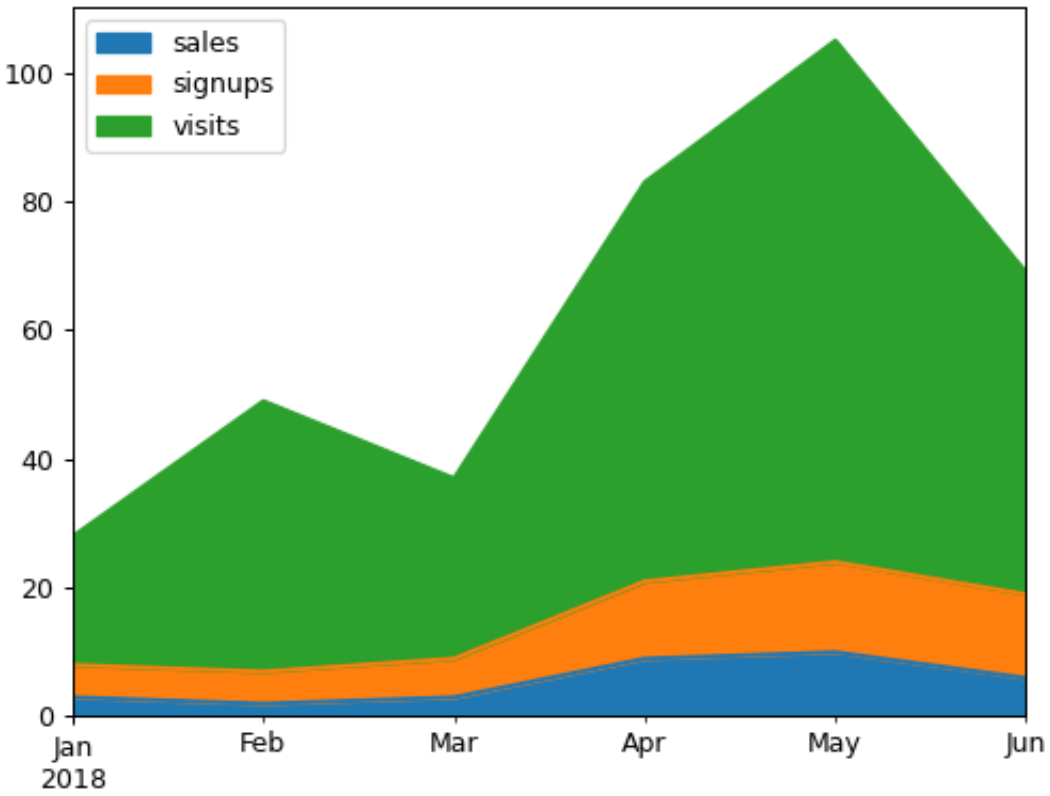
```
>>> ax = df.plot.area(stacked=False)
```

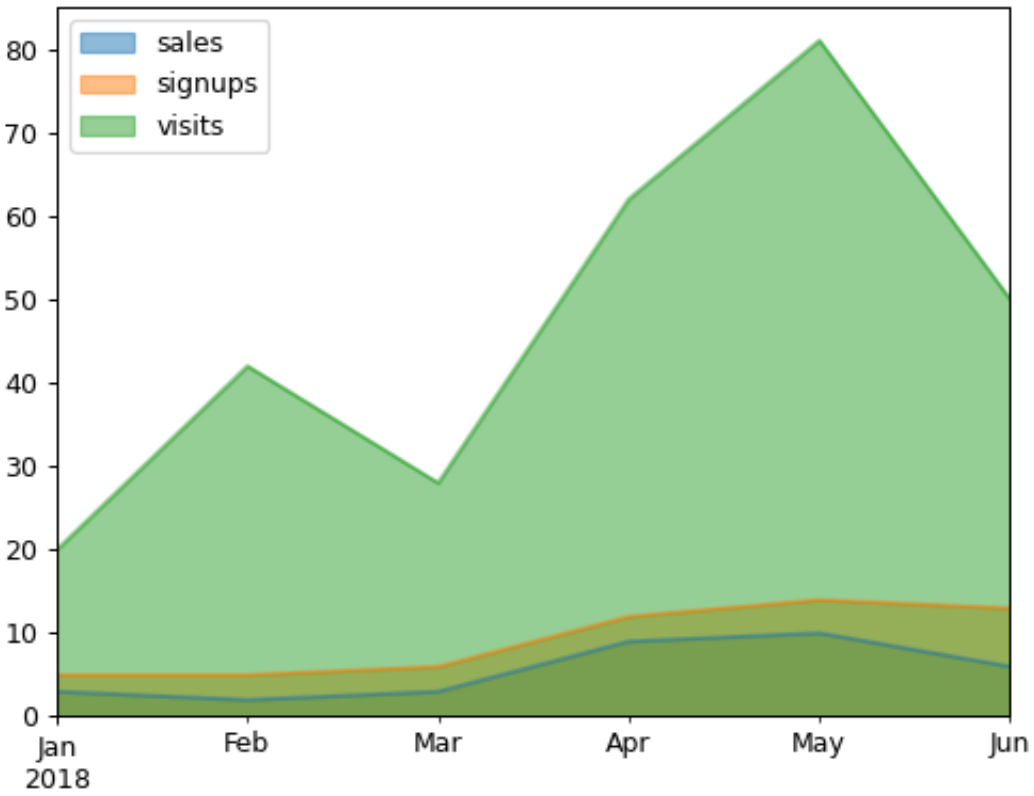
Draw an area plot for a single column:

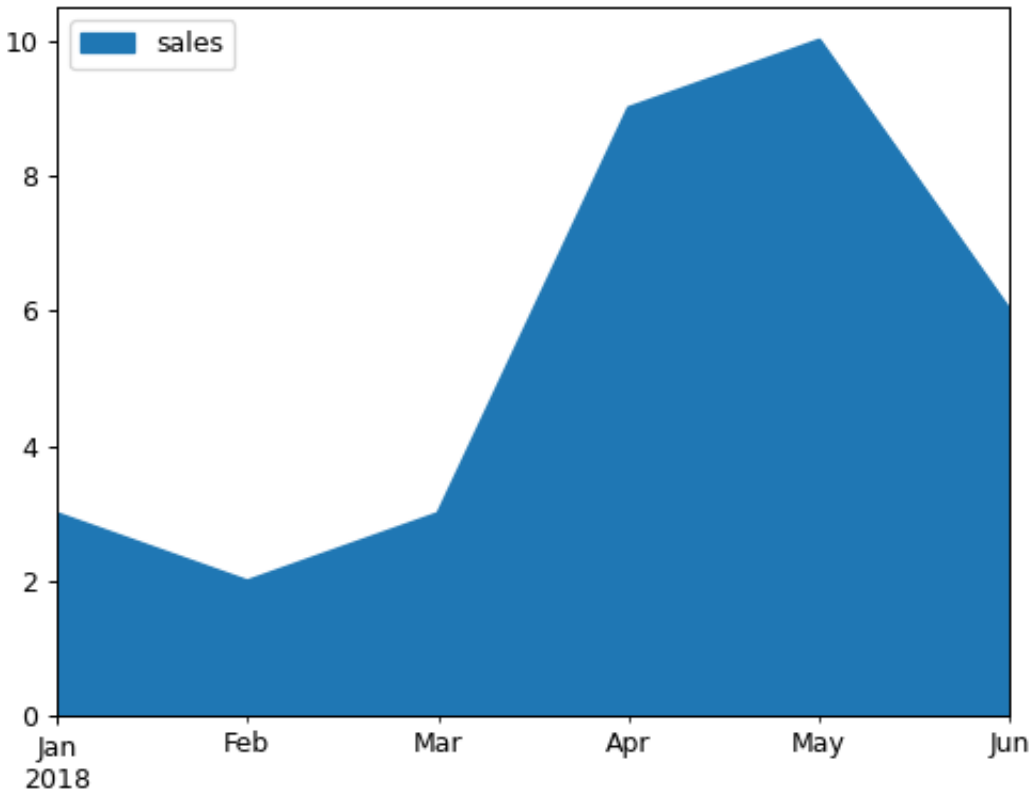
```
>>> ax = df.plot.area(y='sales')
```

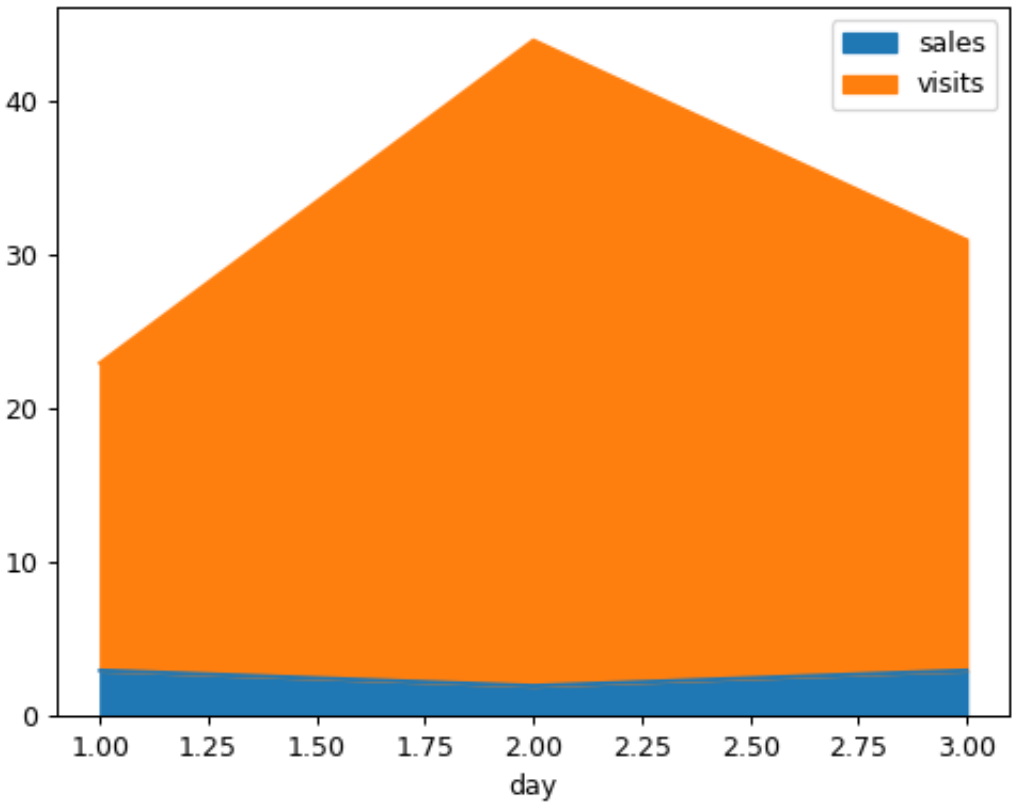
Draw with a different *x*:

```
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3],
...     'visits': [20, 42, 28],
...     'day': [1, 2, 3],
... })
>>> ax = df.plot.area(x='day')
```


sales
signups
visits
100
80
60
40
20
0
Jan
2018
Feb
Mar
Apr
May
Jun


sales
signups
visits
80
70
60
50
40
30
20
10
0
Jan
2018
Feb
Mar
Apr
May
Jun


sales
10
8
6
4
2
0
Jan
2018
Feb
Mar
Apr
May
Jun


sales
visits
40
30
20
10
0
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
day

pandas.Series.plot.bar

`Series.plot.bar(x=None, y=None, **kwargs)`

Vertical bar plot.

A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

Parameters

x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

color [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:

- **A single color string referred to by name, RGB or RGBA code,** for instance 'red' or '#a98d19'.
- **A sequence of color strings referred to by name, RGB or RGBA** code, which will be used for each column recursively. For instance ['green','yellow'] each column's bar will be filled in green or yellow, alternatively.
- **A dict of the form {column name** [color}, so that each column will be] colored accordingly. For example, if your columns are called *a* and *b*, then passing {'a': 'green', 'b': 'red'} will color bars for column *a* in green and bars for column *b* in red.

New in version 1.1.0.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

See also:

DataFrame.plot.barh Horizontal bar plot.
DataFrame.plot Make plots of a DataFrame.
matplotlib.pyplot.bar Make a bar plot with matplotlib.

Examples

Basic plot.

```
>>> df = pd.DataFrame({'lab':['A', 'B', 'C'], 'val':[10, 30, 20]})
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```

Plot a whole dataframe to a bar plot. Each column is assigned a distinct color, and each row is nested in a group along the horizontal axis.

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
```

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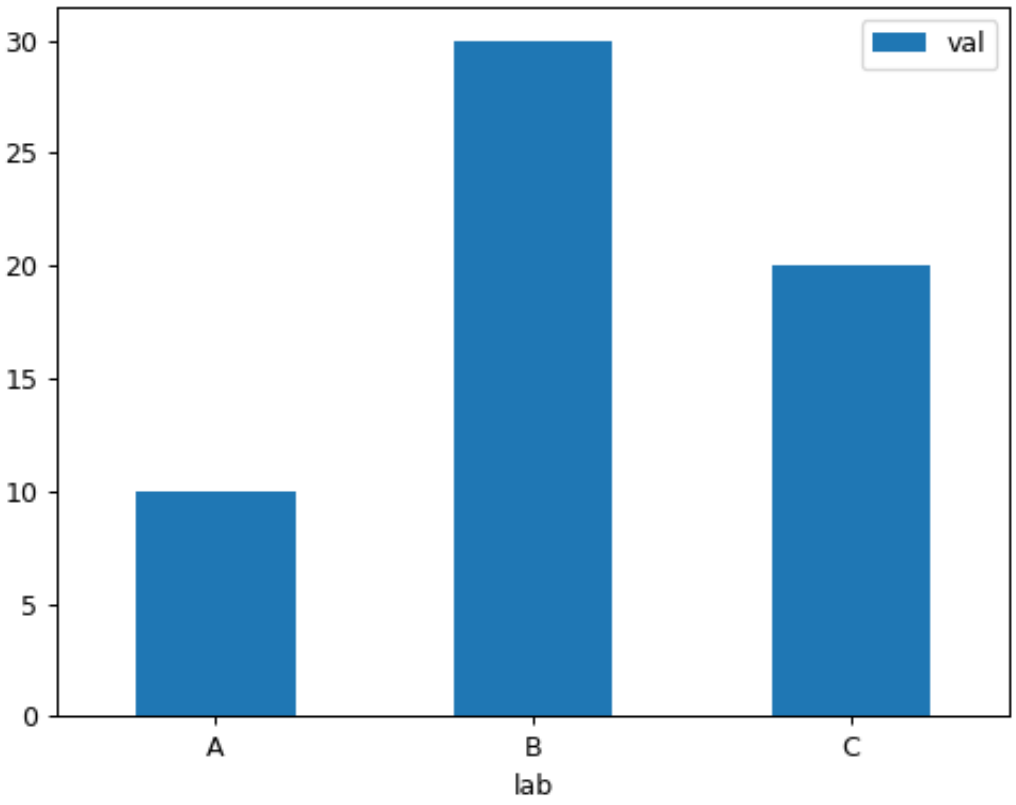
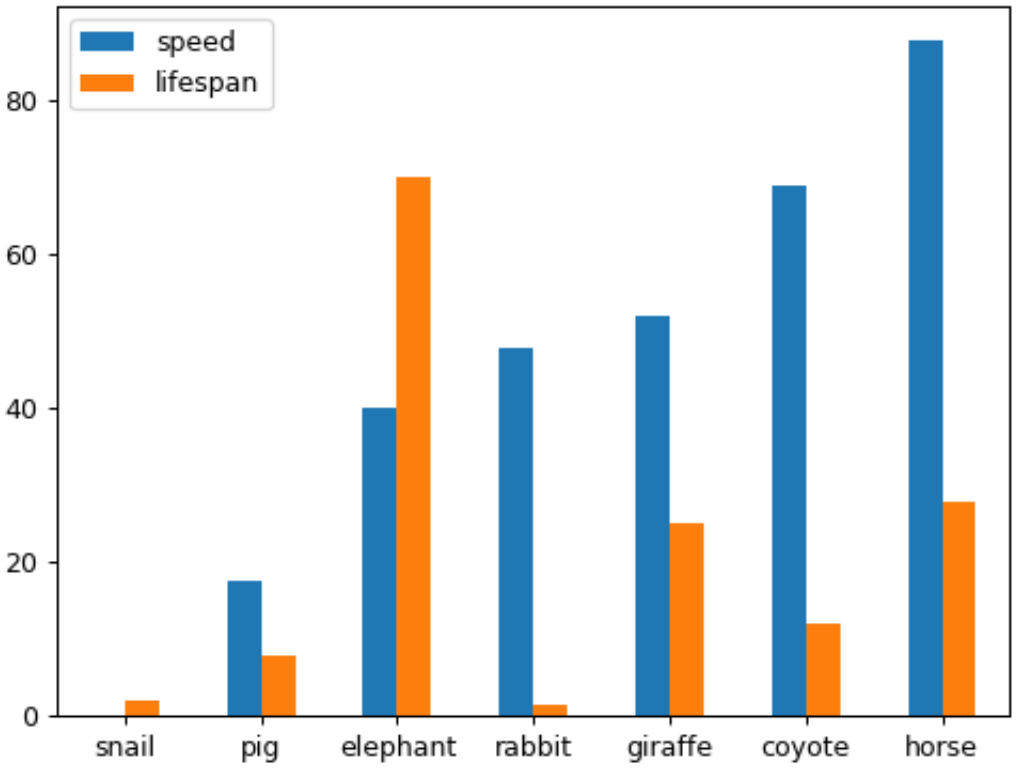

val
30
25
20
15
10
5
0
A
B
C
lab

(continued from previous page)

```
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.bar(rot=0)
```



Plot stacked bar charts for the DataFrame

```
>>> ax = df.plot.bar(stacked=True)
```

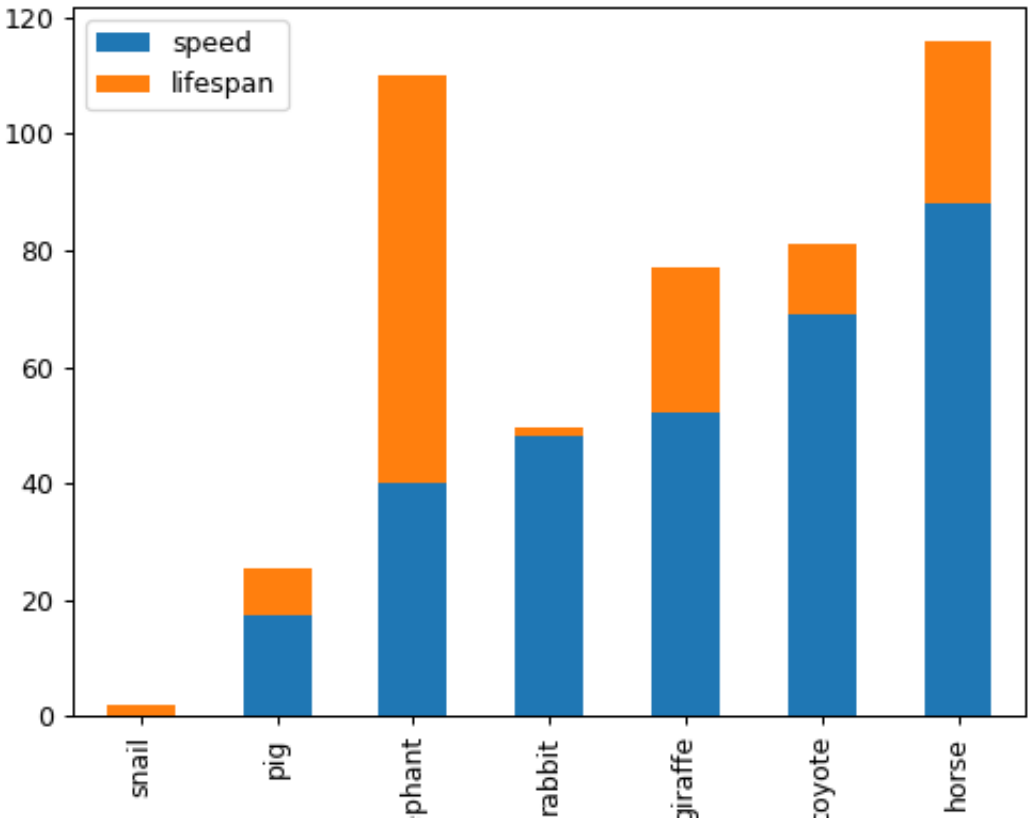
Instead of nesting, the figure can be split by column with `subplots=True`. In this case, a `numpy.ndarray` of `matplotlib.axes.Axes` are returned.

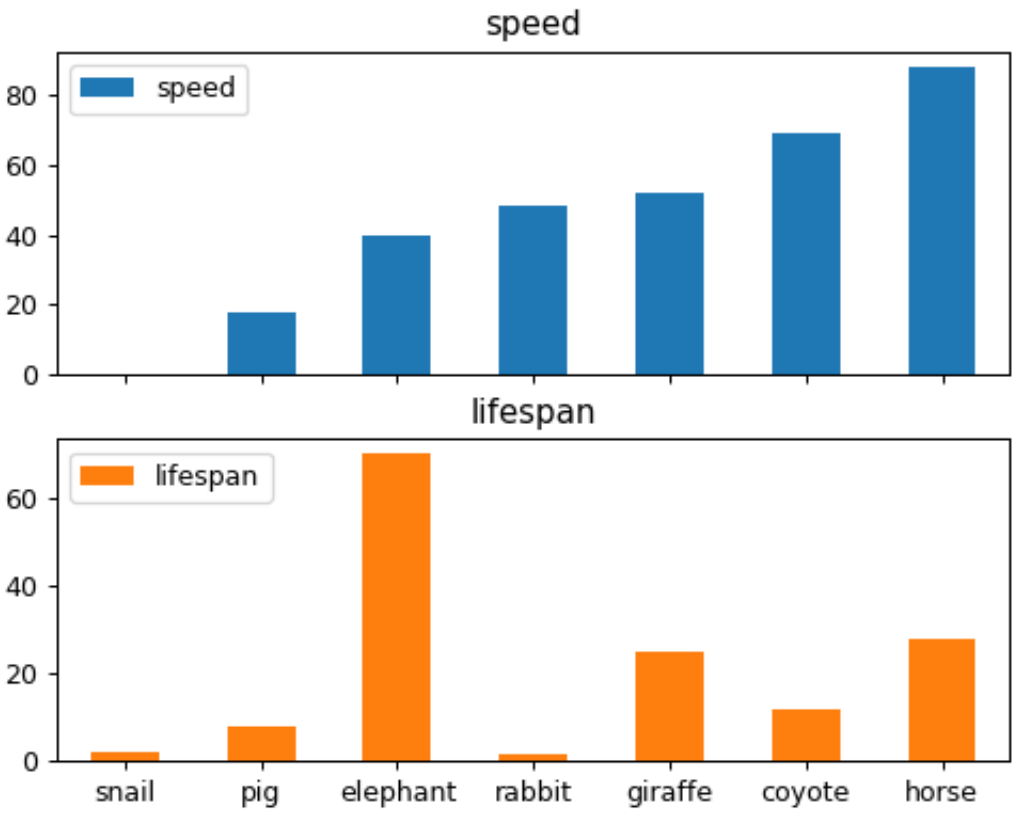
```
>>> axes = df.plot.bar(rot=0, subplots=True)
>>> axes[1].legend(loc=2)
```

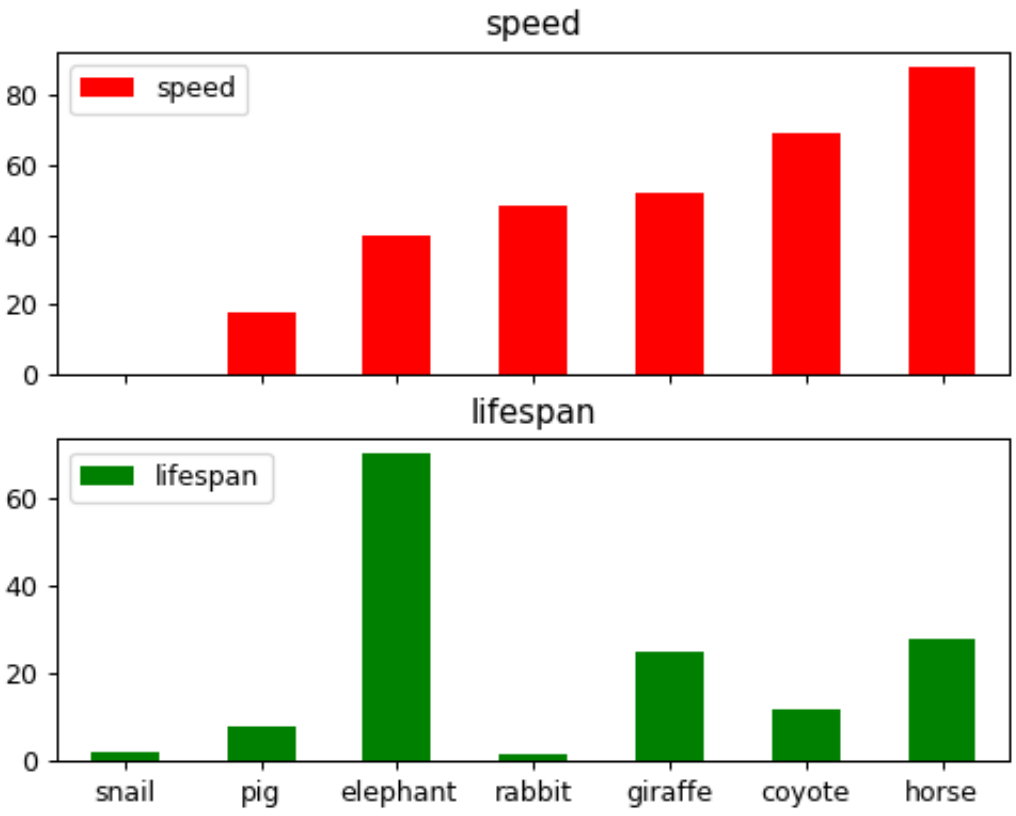
If you don't like the default colours, you can specify how you'd like each column to be colored.

```
>>> axes = df.plot.bar(
...     rot=0, subplots=True, color={"speed": "red", "lifespan": "green"}
... )
>>> axes[1].legend(loc=2)
```

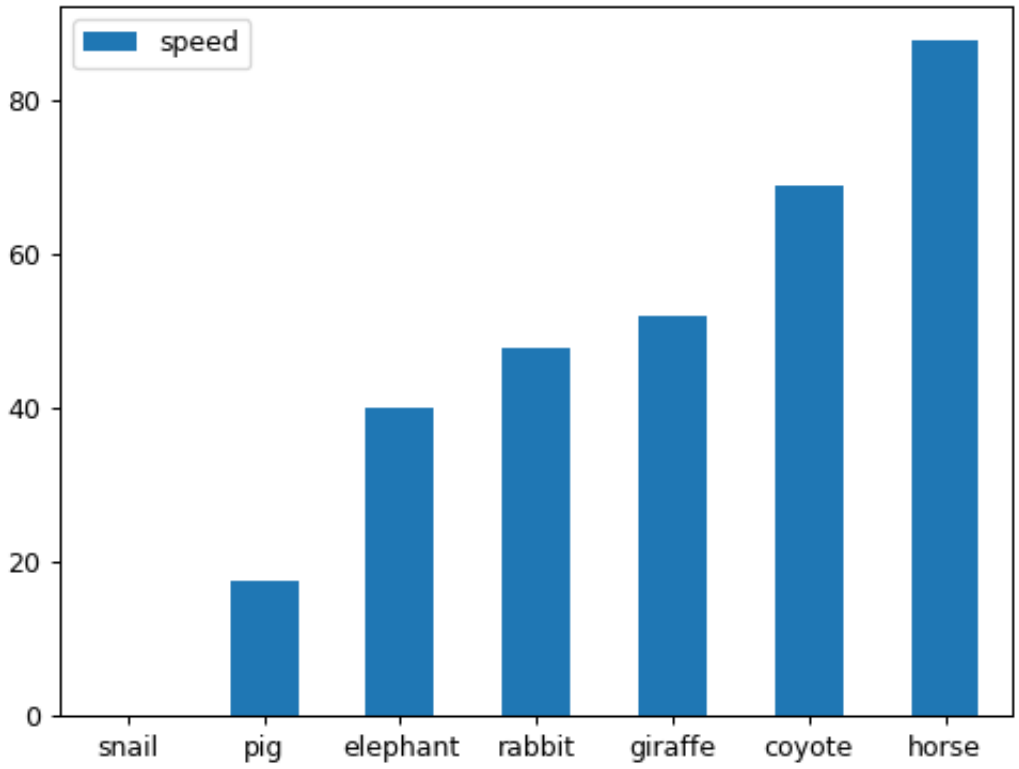
Plot a single column.


120
100
80
60
40
20
0
speed
lifespan
snail
pig
phant
rabbit
giraffe
oyote
horse


speed
speed
80
60
40
20
0
lifespan
lifespan
60
40
20
0
snail
pig
elephant
rabbit
giraffe
coyote
horse


speed
speed
80
60
40
20
0
lifespan
lifespan
60
40
20
0
snail
pig
elephant
rabbit
giraffe
coyote
horse

```
>>> ax = df.plot.bar(y='speed', rot=0)
```



Plot only selected categories for the DataFrame.

```
>>> ax = df.plot.bar(x='lifespan', rot=0)
```

pandas.Series.plot.barh

`Series.plot.`**`barh`**(*x=None*, *y=None*, ***kwargs*)

Make a horizontal bar plot.

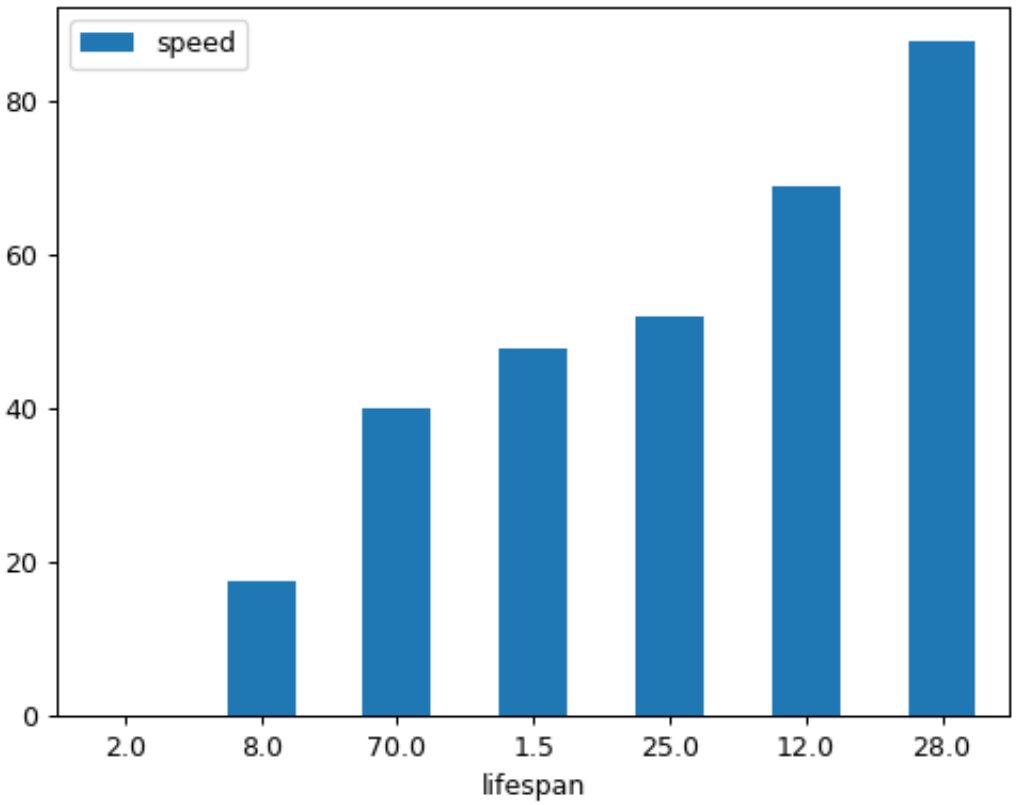
A horizontal bar plot is a plot that presents quantitative data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

Parameters

x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

color [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:


speed
80
60
40
20
0
2.0
8.0
70.0
1.5
25.0
12.0
28.0
lifespan

- **A single color string referred to by name, RGB or RGBA code,** for instance 'red' or '#a98d19'.
- **A sequence of color strings referred to by name, RGB or RGBA** code, which will be used for each column recursively. For instance ['green','yellow'] each column's bar will be filled in green or yellow, alternatively.
- **A dict of the form {column name** [color}, so that each column will be] colored accordingly. For example, if your columns are called *a* and *b*, then passing {'a': 'green', 'b': 'red'} will color bars for column *a* in green and bars for column *b* in red.

New in version 1.1.0.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

See also:

DataFrame.plot.bar Vertical bar plot.
DataFrame.plot Make plots of DataFrame using matplotlib.
matplotlib.axes.Axes.bar Plot a vertical bar plot using matplotlib.

Examples

Basic example

```
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})
>>> ax = df.plot.barh(x='lab', y='val')
```

Plot a whole DataFrame to a horizontal bar plot

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh()
```

Plot stacked barh charts for the DataFrame

```
>>> ax = df.plot.barh(stacked=True)
```

We can specify colors for each column

```
>>> ax = df.plot.barh(color={"speed": "red", "lifespan": "green"})
```

Plot a column of the DataFrame to a horizontal bar plot

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
```

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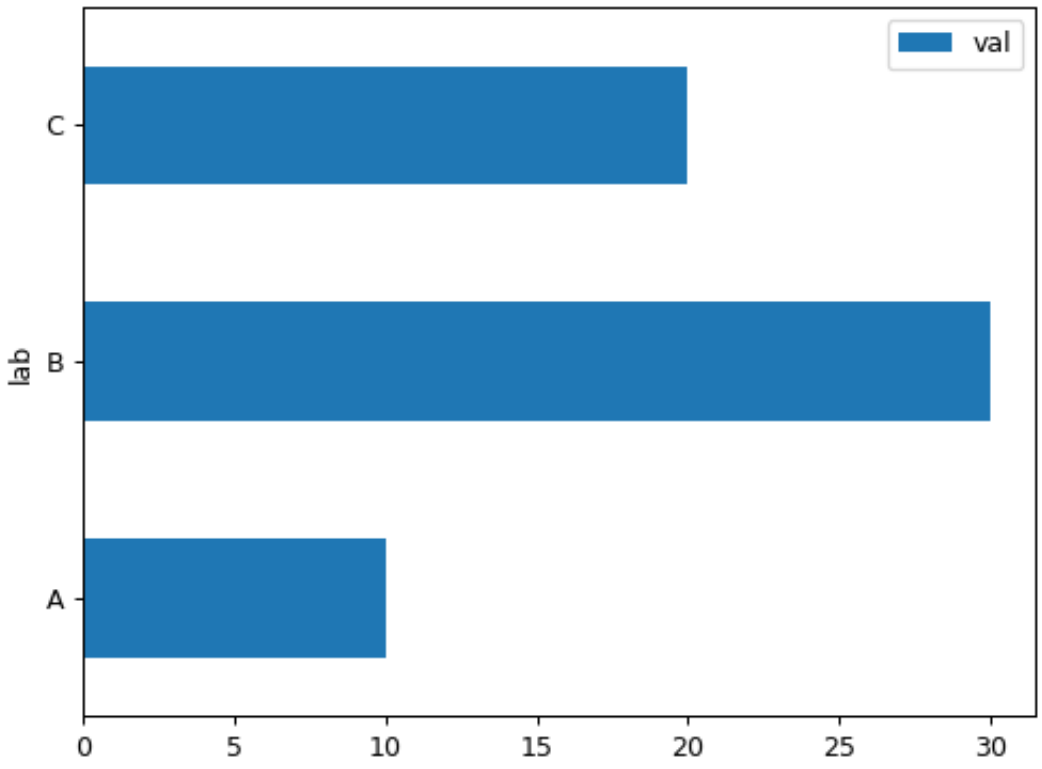
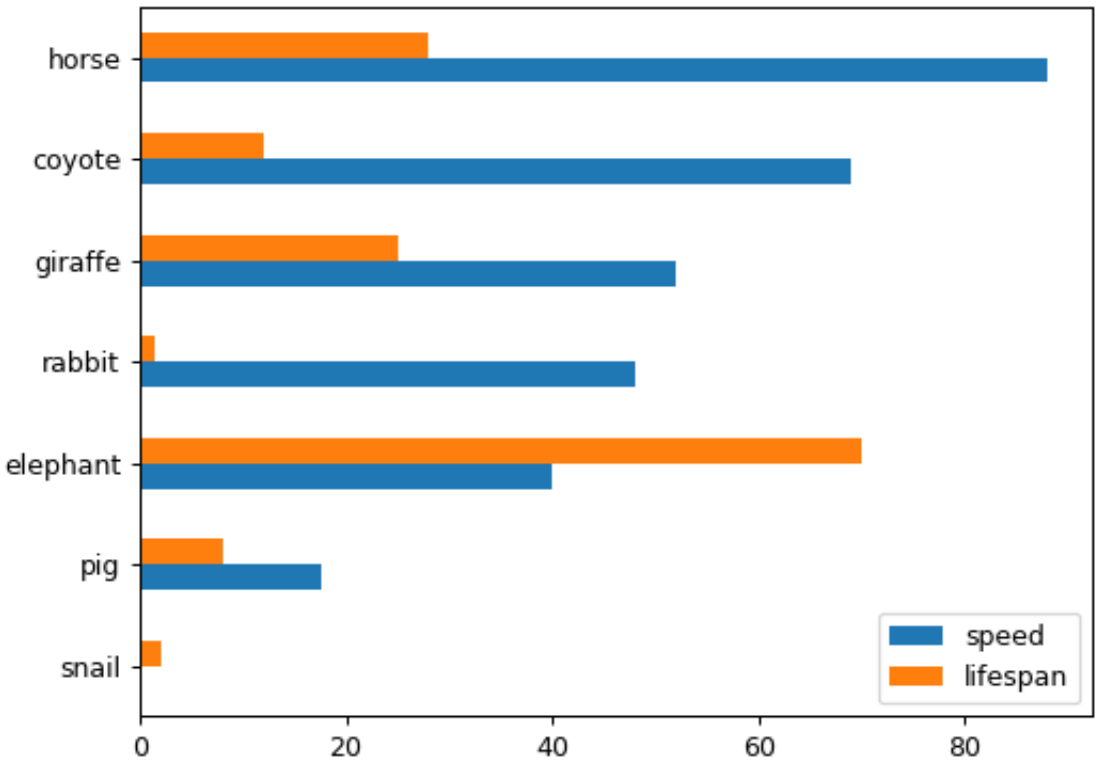
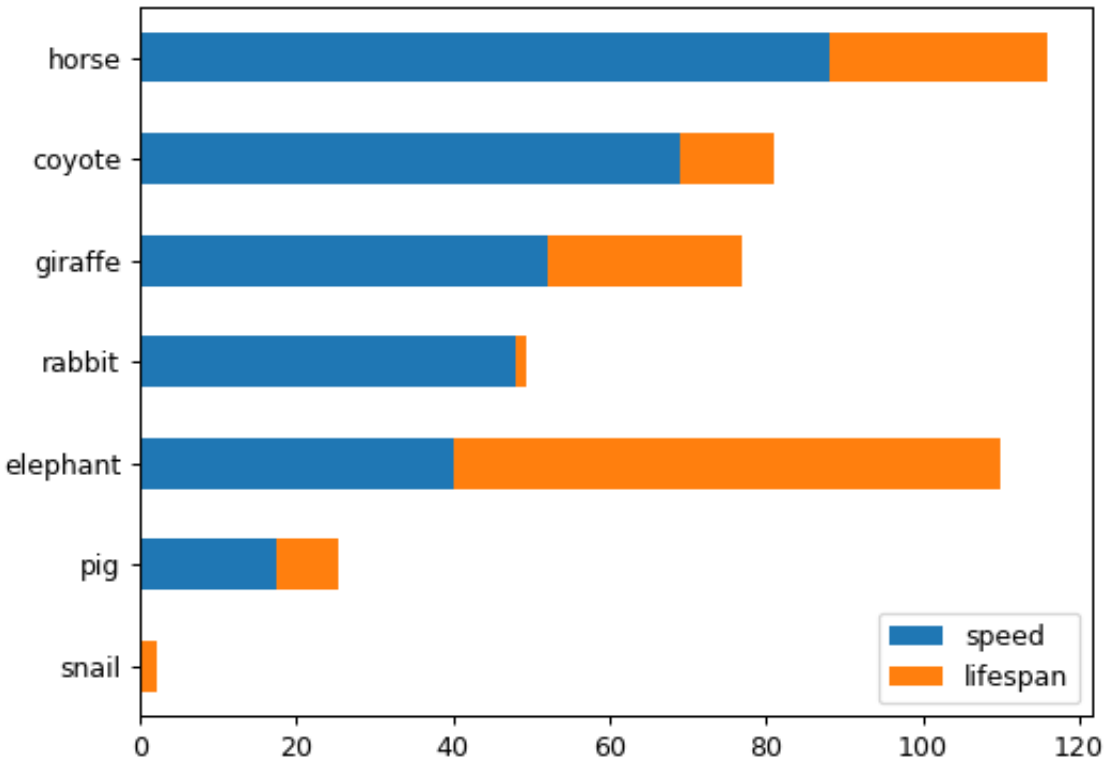
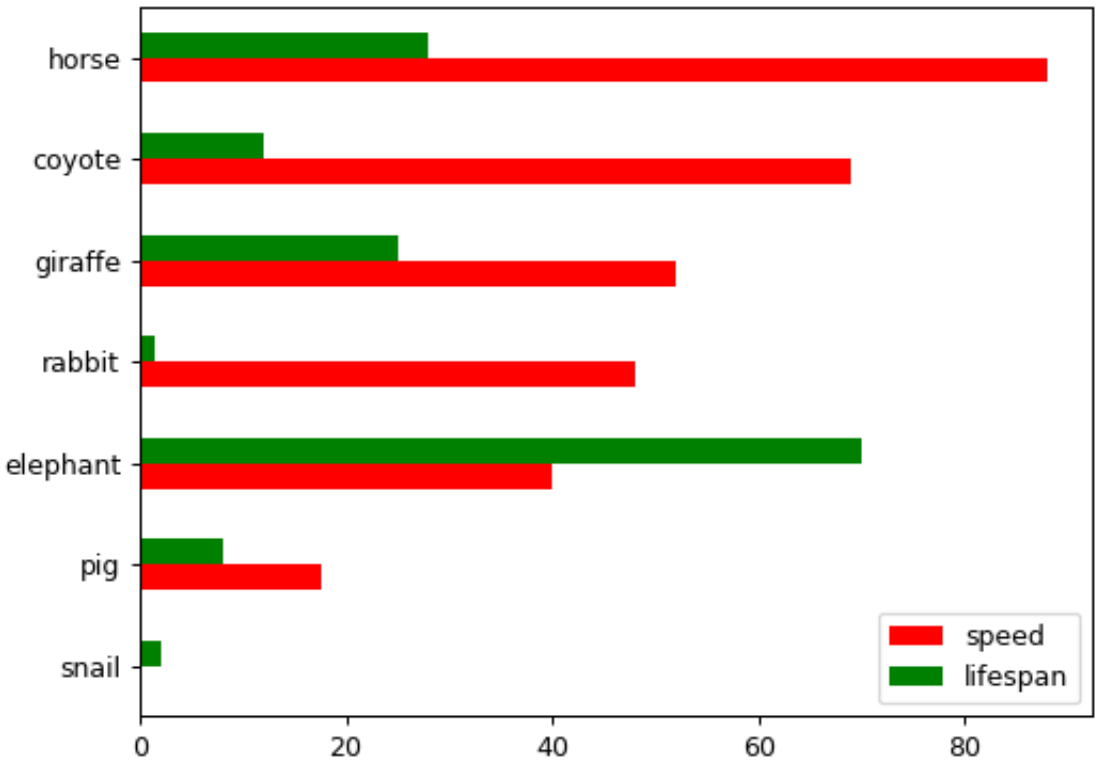

val
C
B
A
lab
0
5
10
15
20
25
30

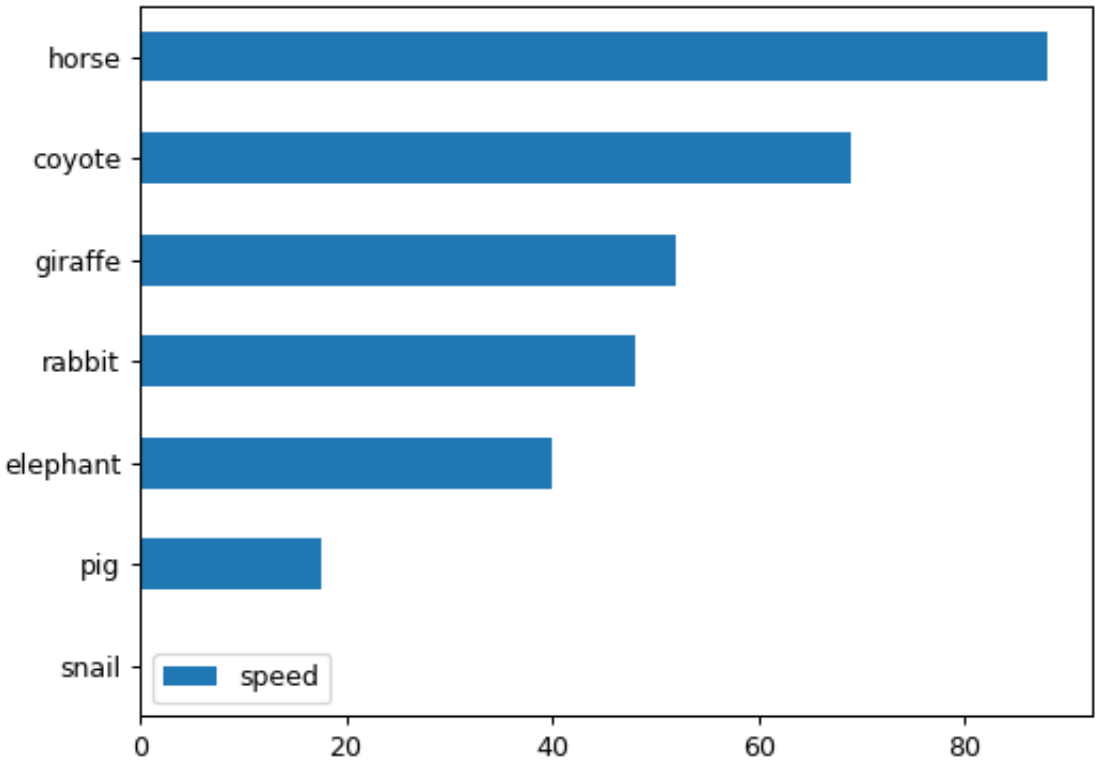

horse
coyote
giraffe
rabbit
elephant
pig
snail
0
20
40
60
80
speed
lifespan


horse
coyote
giraffe
rabbit
elephant
pig
snail
0
20
40
60
80
100
120
speed
lifespan


horse
coyote
giraffe
rabbit
elephant
pig
snail
0
20
40
60
80
speed
lifespan

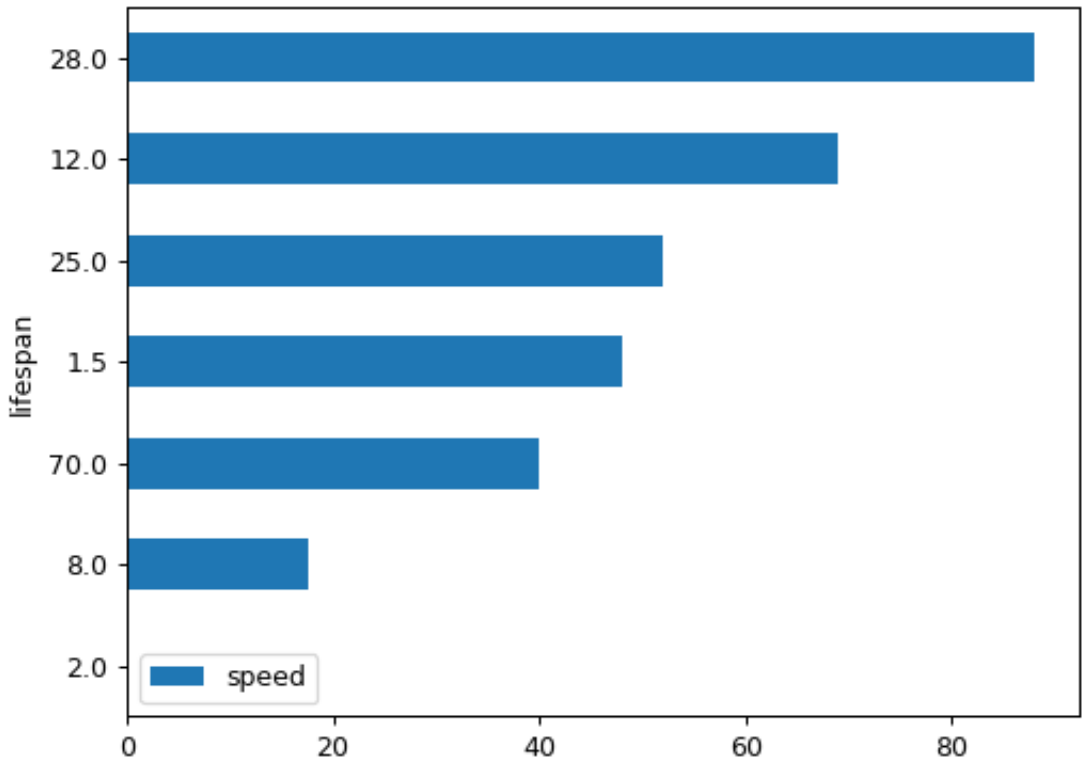
(continued from previous page)

```
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(y='speed')
```



Plot DataFrame versus the desired column

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(x='lifespan')
```


28.0
12.0
25.0
1.5
70.0
8.0
2.0
lifespan
speed
0
20
40
60
80

pandas.Series.plot.box

Series.plot.**box**(*by=None*, ***kwargs*)

Make a box plot of the DataFrame columns.

A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to 1.5*IQR (IQR = Q3 - Q1) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia's entry for boxplot.

A consideration when using this chart is that the box and the whiskers can overlap, which is very common when plotting small sets of data.

Parameters

by [str or sequence] Column in the DataFrame to group by.

****kwargs** Additional keywords are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or numpy.ndarray of them

See also:

DataFrame.boxplot Another method to draw a box plot.
Series.plot.box Draw a box plot from a Series object.
matplotlib.pyplot.boxplot Draw a box plot in matplotlib.

Examples

Draw a box plot from a DataFrame with four columns of randomly generated data.

```
>>> data = np.random.randn(25, 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'))
>>> ax = df.plot.box()
```

pandas.Series.plot.density

Series.plot.**density**(*bw_method=None*, *ind=None*, ***kwargs*)

Generate Kernel Density Estimate plot using Gaussian kernels.

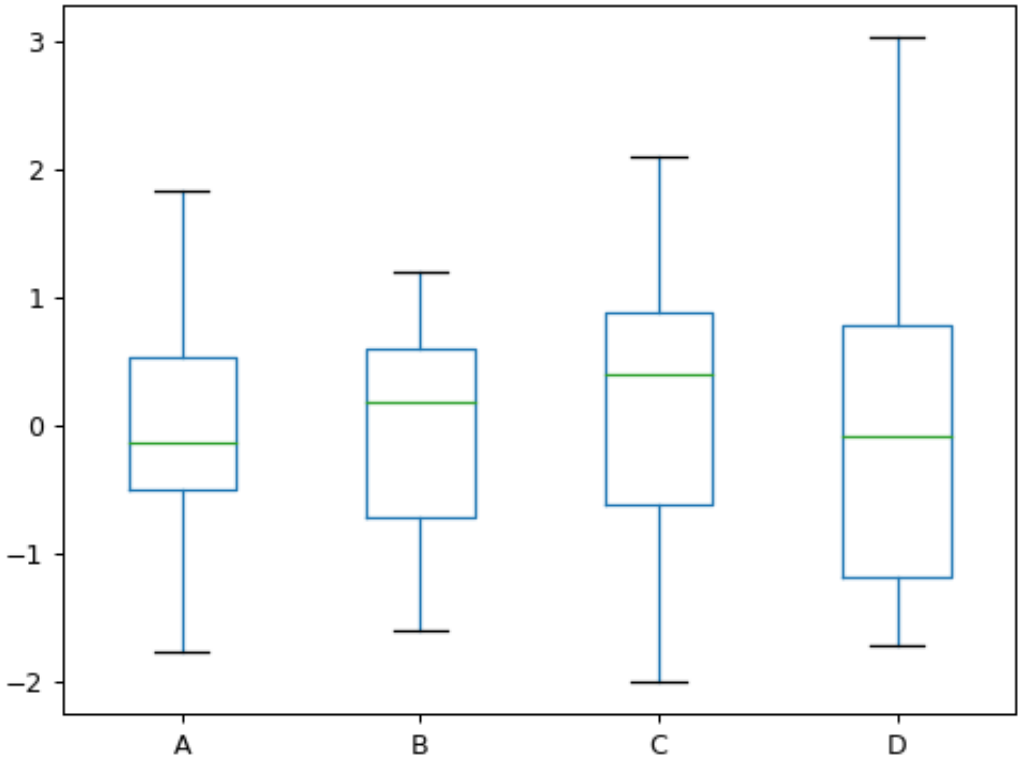
In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

Parameters

bw_method [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be 'scott', 'silverman', a scalar constant or a callable. If None (default), 'scott' is used. See scipy.stats.gaussian_kde for more information.

ind [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

****kwargs** Additional keyword arguments are documented in pandas.%(this-datatype)s.plot().


3
2
1
0
−1
−2
A
B
C
D

Returns

matplotlib.axes.Axes or numpy.ndarray of them

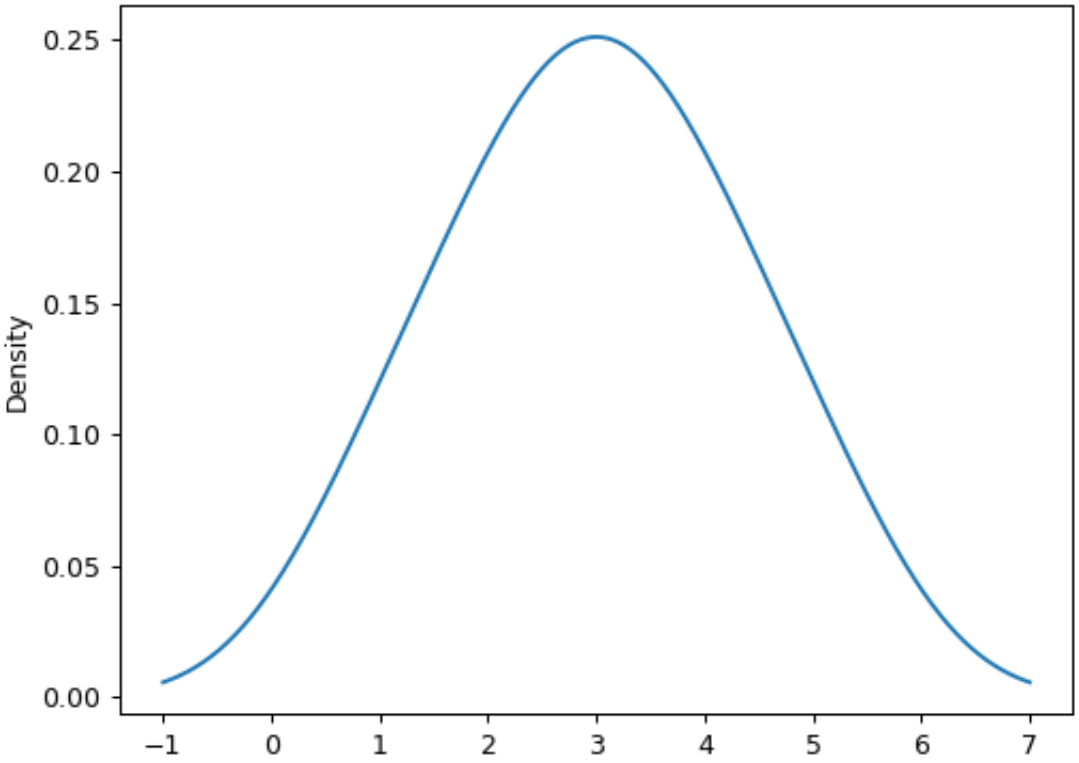
See also:

`scipy.stats.gaussian_kde` Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

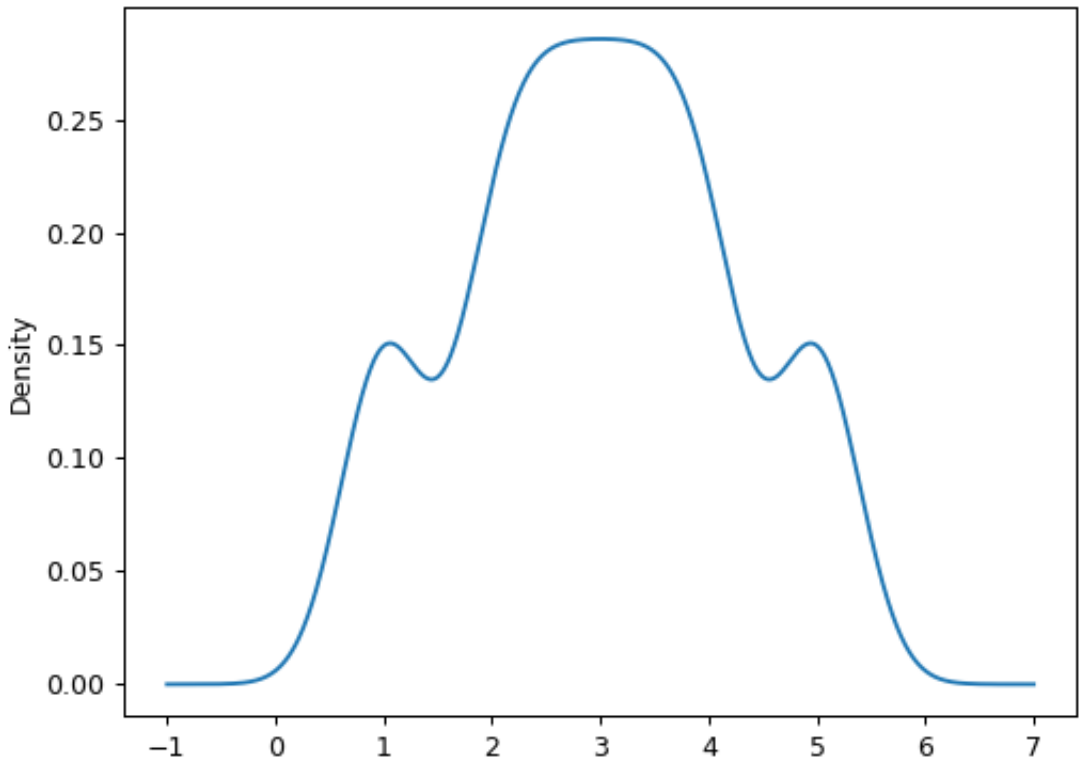


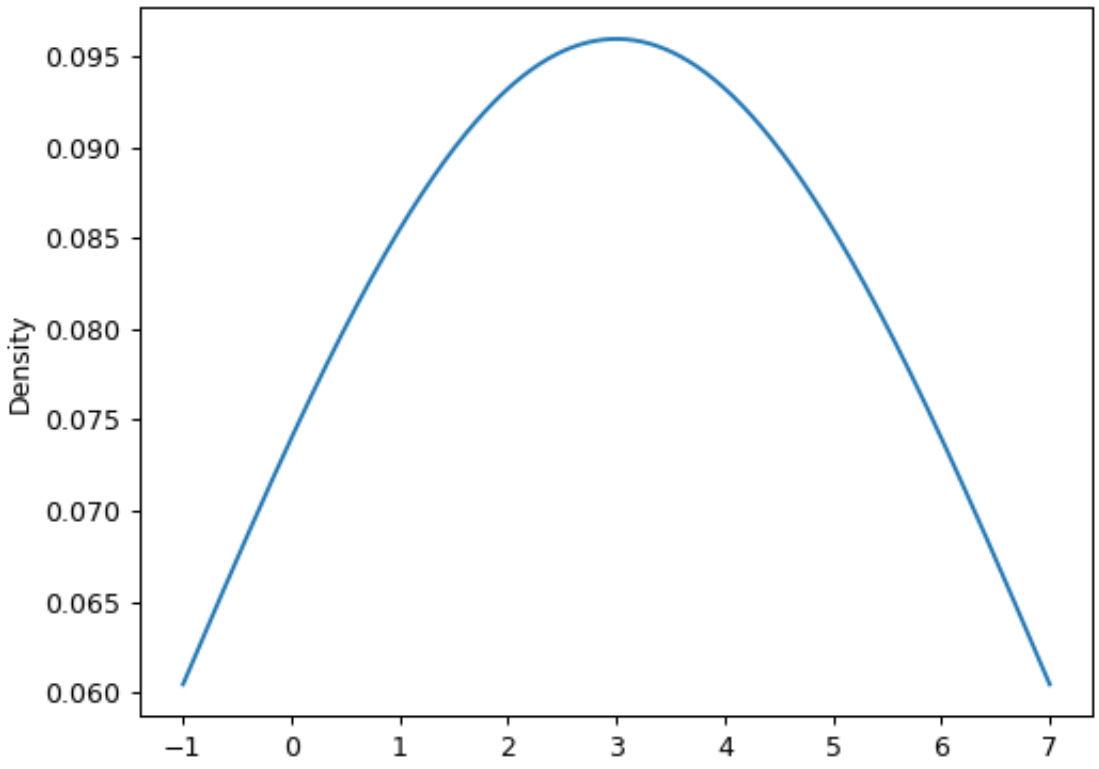
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

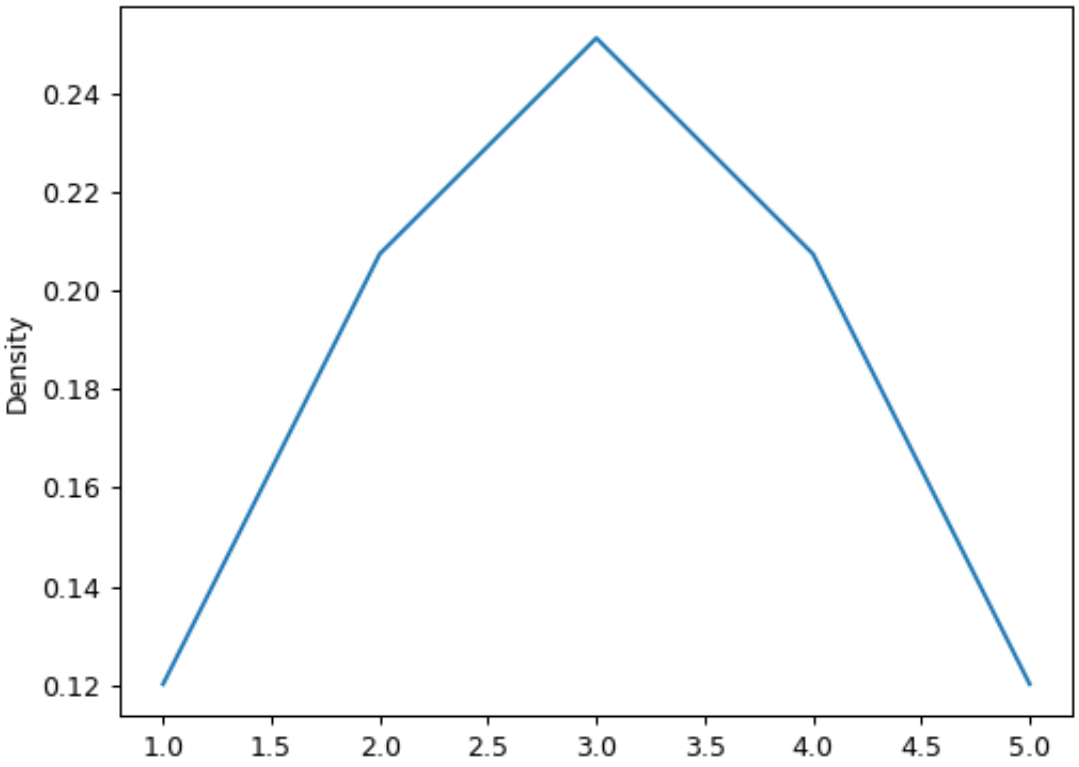
```
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:


Density
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7


0.095
0.090
0.085
0.080
0.075
0.070
0.065
0.060
Density
−1
0
1
2
3
4
5
6
7

```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```



For DataFrame, it works in the same way:

```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```

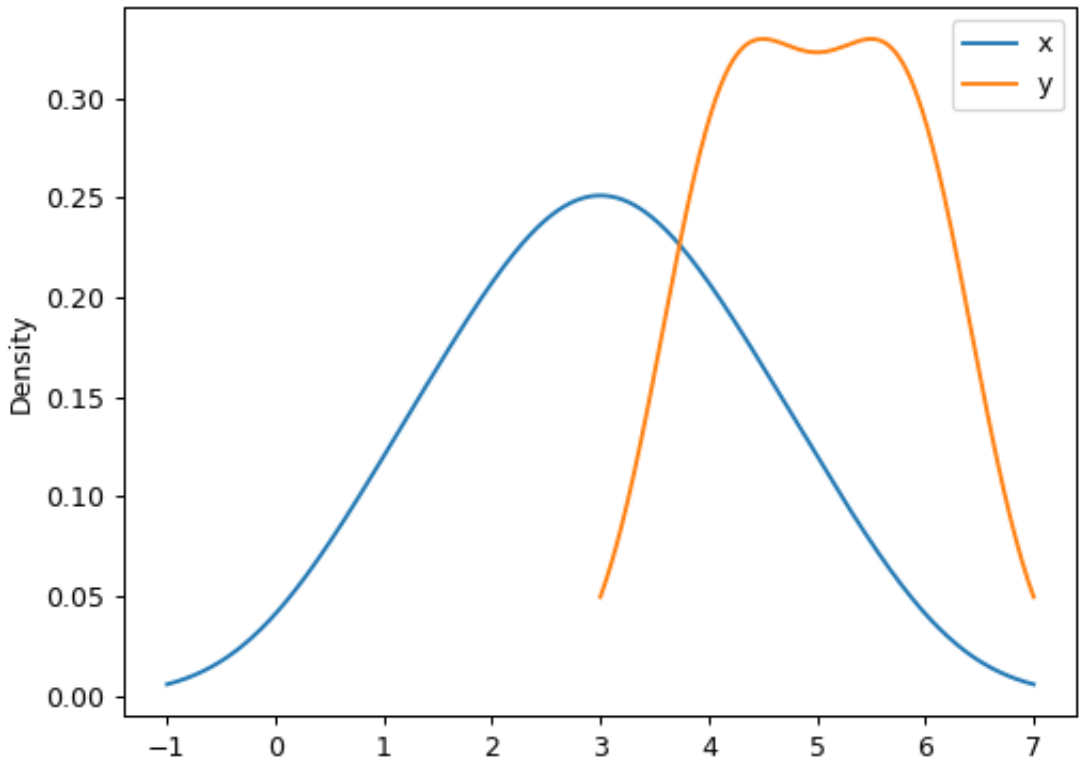
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

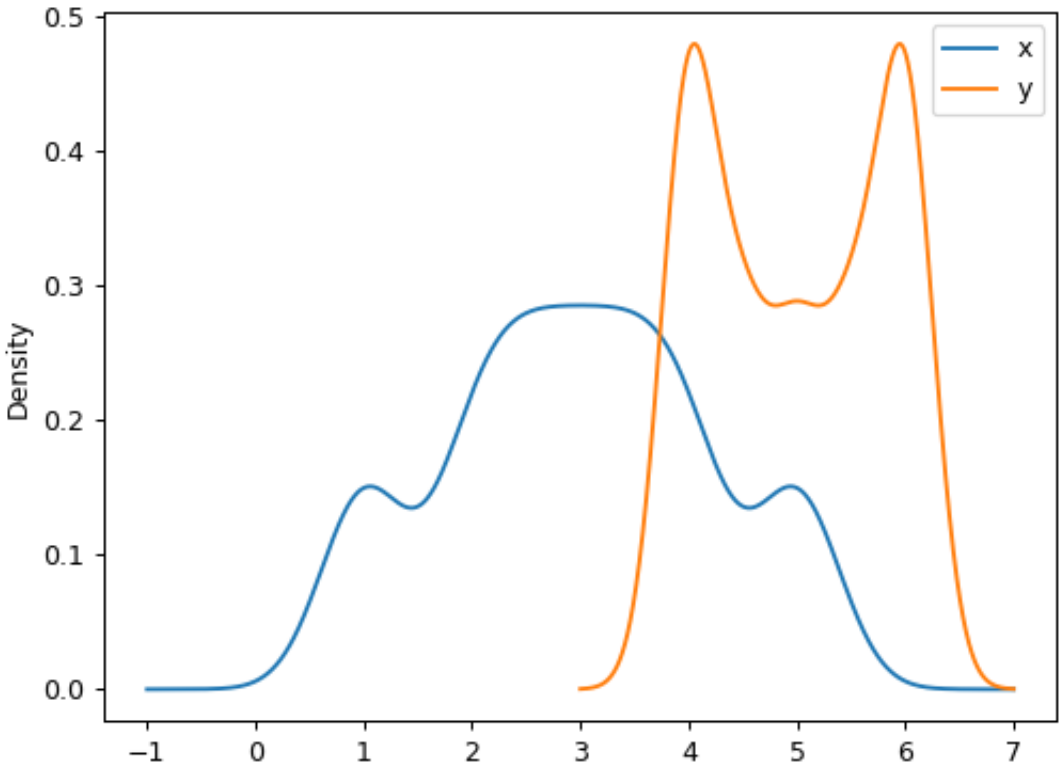
```
>>> ax = df.plot.kde(bw_method=0.3)
```

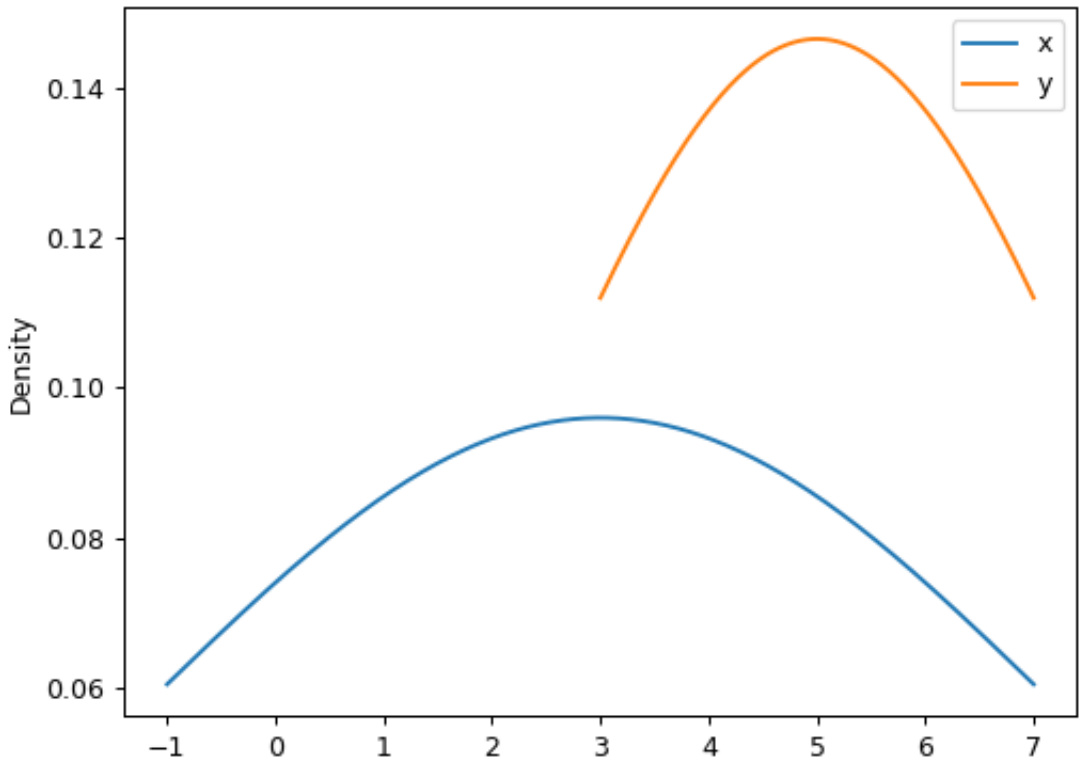
```
>>> ax = df.plot.kde(bw_method=3)
```

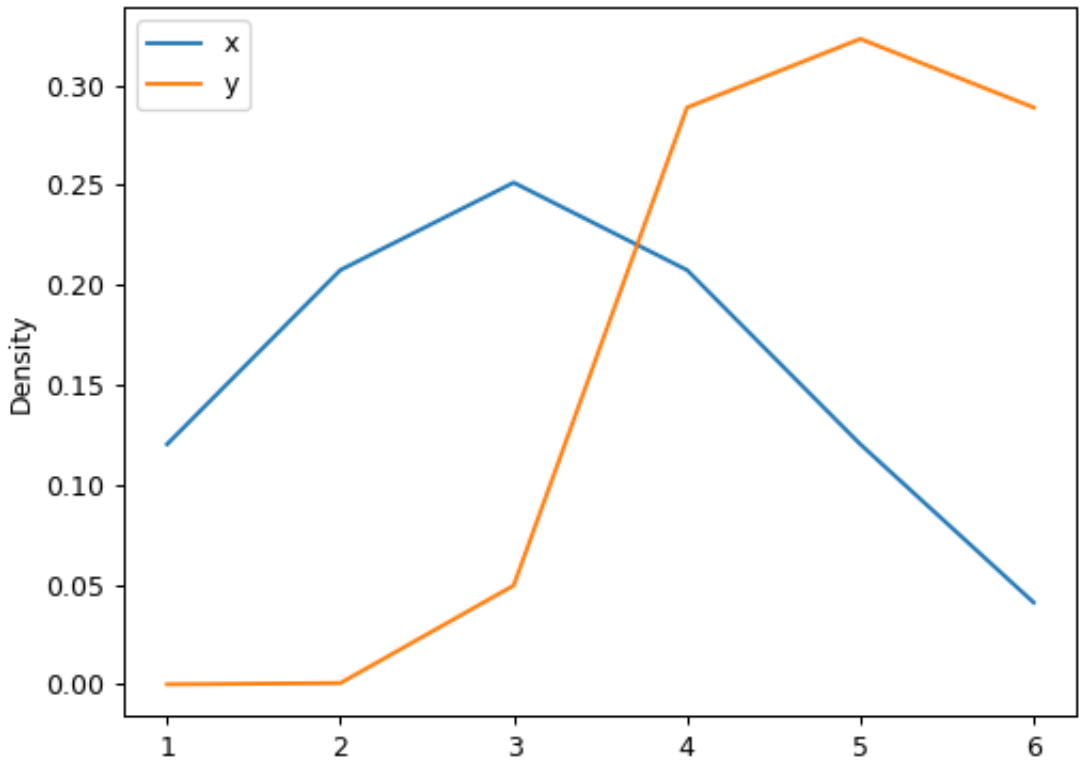
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```


x
y
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7


0.5
0.4
0.3
0.2
0.1
0.0
Density
−1
0
1
2
3
4
5
6
7
x
y


x
y
0.14
0.12
0.10
0.08
0.06
Density
−1
0
1
2
3
4
5
6
7


x
y
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
1
2
3
4
5
6

pandas.Series.plot.hist

Series.plot.**hist**(*by=None*, *bins=10*, ***kwargs*)

Draw one histogram of the DataFrame's columns.

A histogram is a representation of the distribution of data. This function groups the values of all given Series in the DataFrame into bins and draws all bins in one matplotlib.axes.Axes. This is useful when the DataFrame's Series are in a similar scale.

Parameters

by [str or sequence, optional] Column in the DataFrame to group by.

bins [int, default 10] Number of histogram bins to be used.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

class:*matplotlib.AxesSubplot* Return a histogram plot.

See also:

DataFrame.hist Draw histograms per DataFrame's Series.
Series.hist Draw a histogram with Series' data.

Examples

When we draw a dice 6000 times, we expect to get each value around 1000 times. But when we draw two dices and sum the result, the distribution is going to be quite different. A histogram illustrates those distributions.

```
>>> df = pd.DataFrame(
...     np.random.randint(1, 7, 6000),
...     columns = ['one'])
>>> df['two'] = df['one'] + np.random.randint(1, 7, 6000)
>>> ax = df.plot.hist(bins=12, alpha=0.5)
```

pandas.Series.plot.kde

Series.plot.**kde**(*bw_method=None*, *ind=None*, ***kwargs*)

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

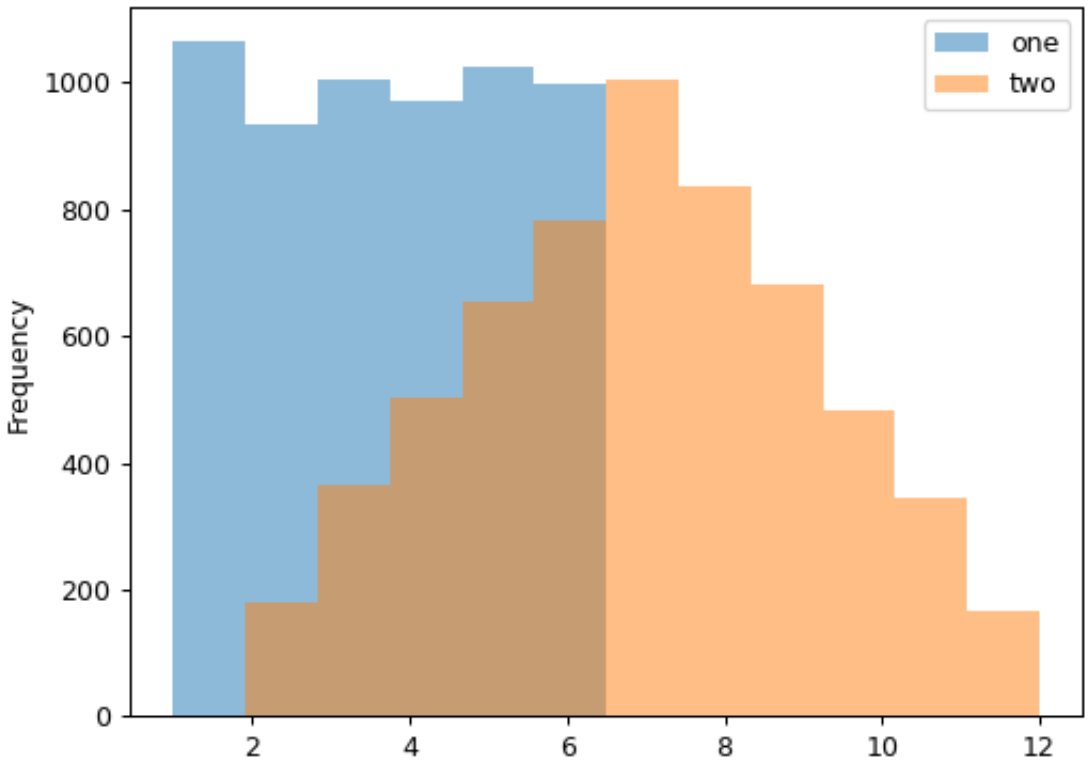
Parameters

bw_method [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be 'scott', 'silverman', a scalar constant or a callable. If None (default), 'scott' is used. See scipy.stats.gaussian_kde for more information.

ind [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

****kwargs** Additional keyword arguments are documented in pandas.%(this-datatype)s.plot().

Returns


one
two
Frequency
0
200
400
600
800
1000
2
4
6
8
10
12

matplotlib.axes.Axes or numpy.ndarray of them

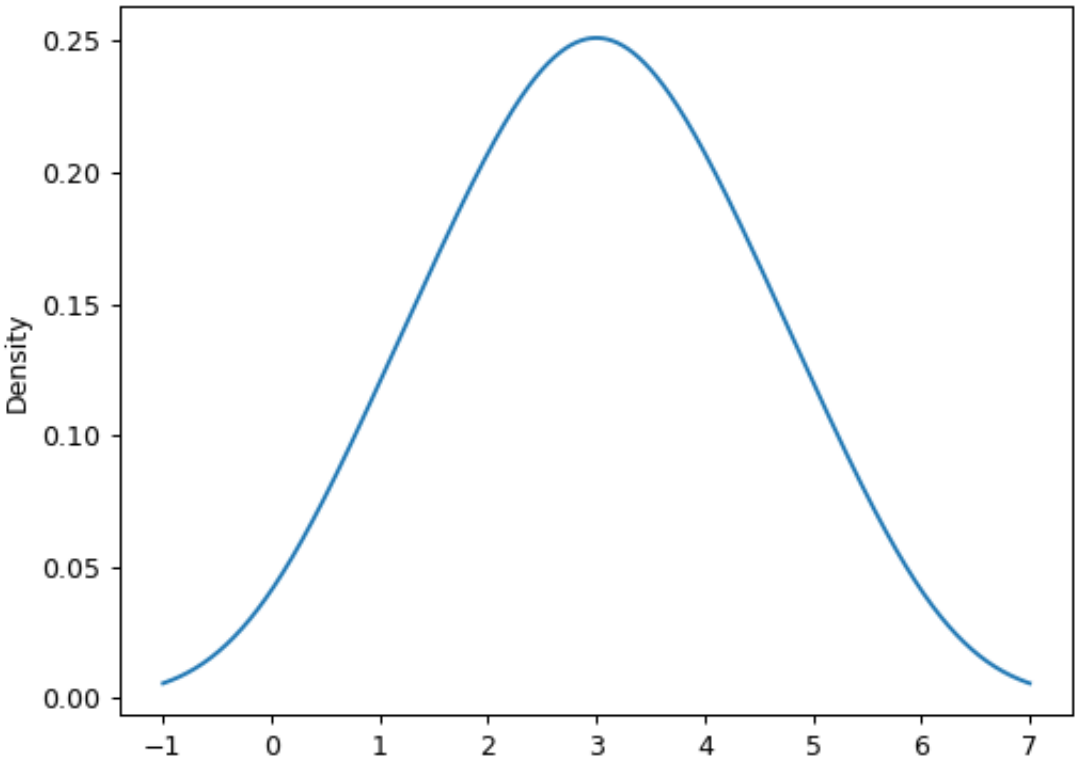
See also:

`scipy.stats.gaussian_kde` Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

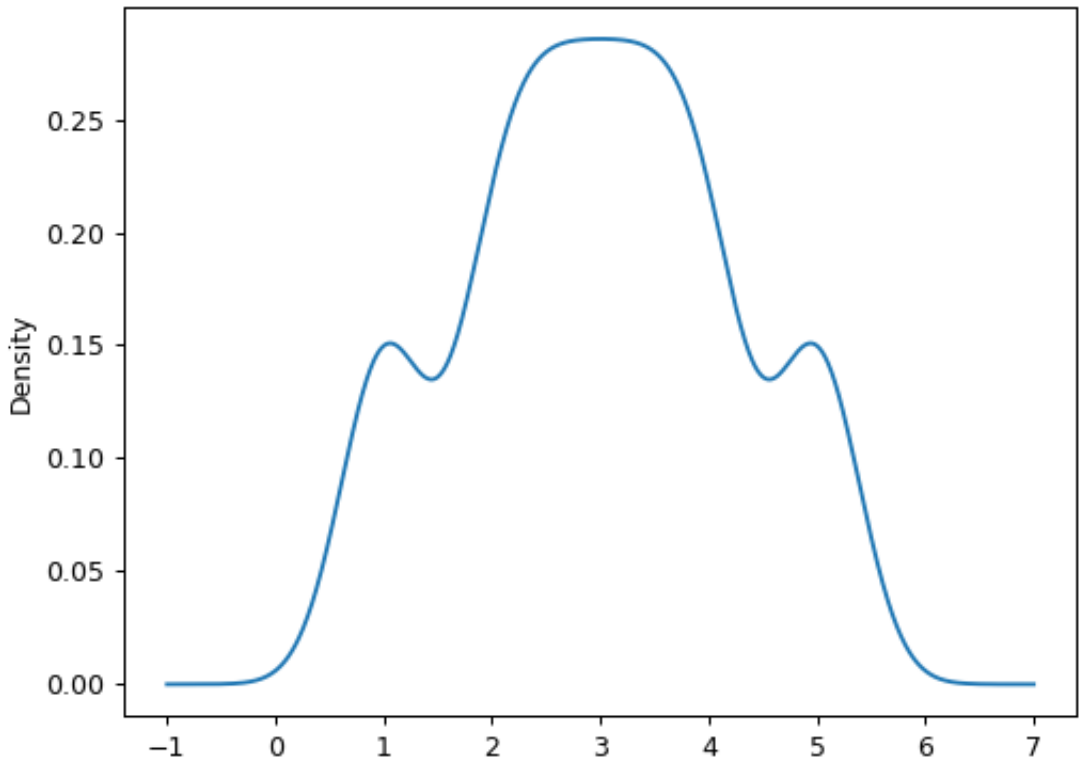


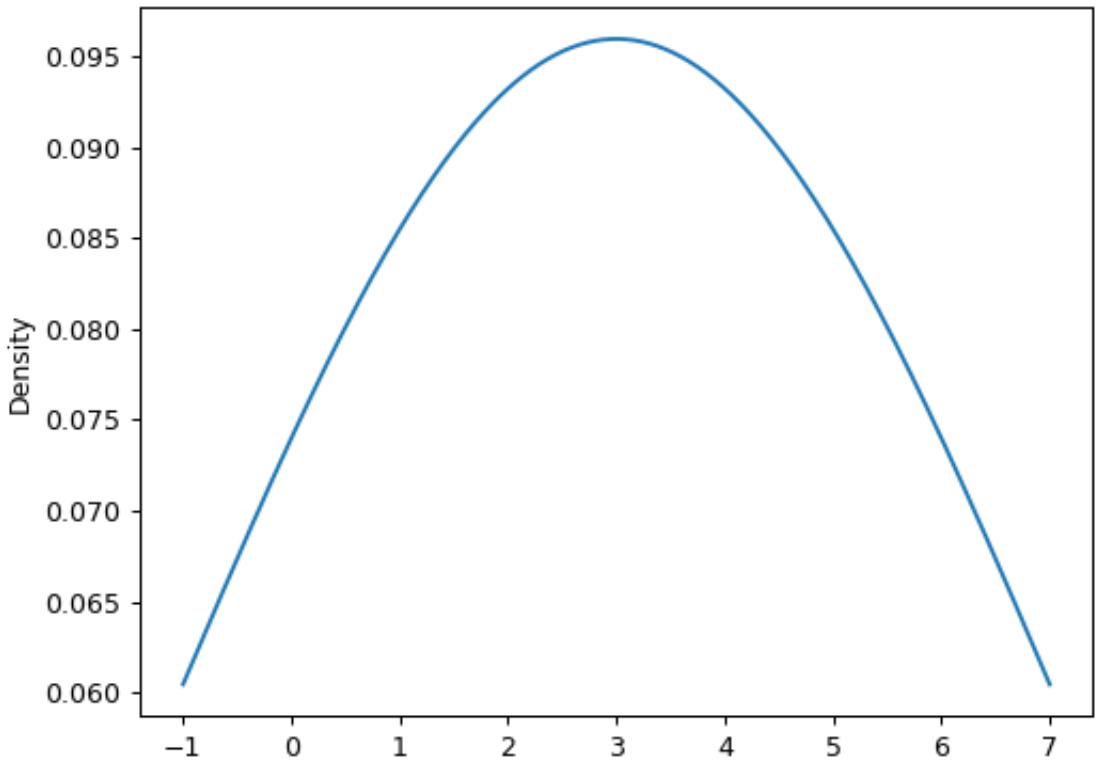
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

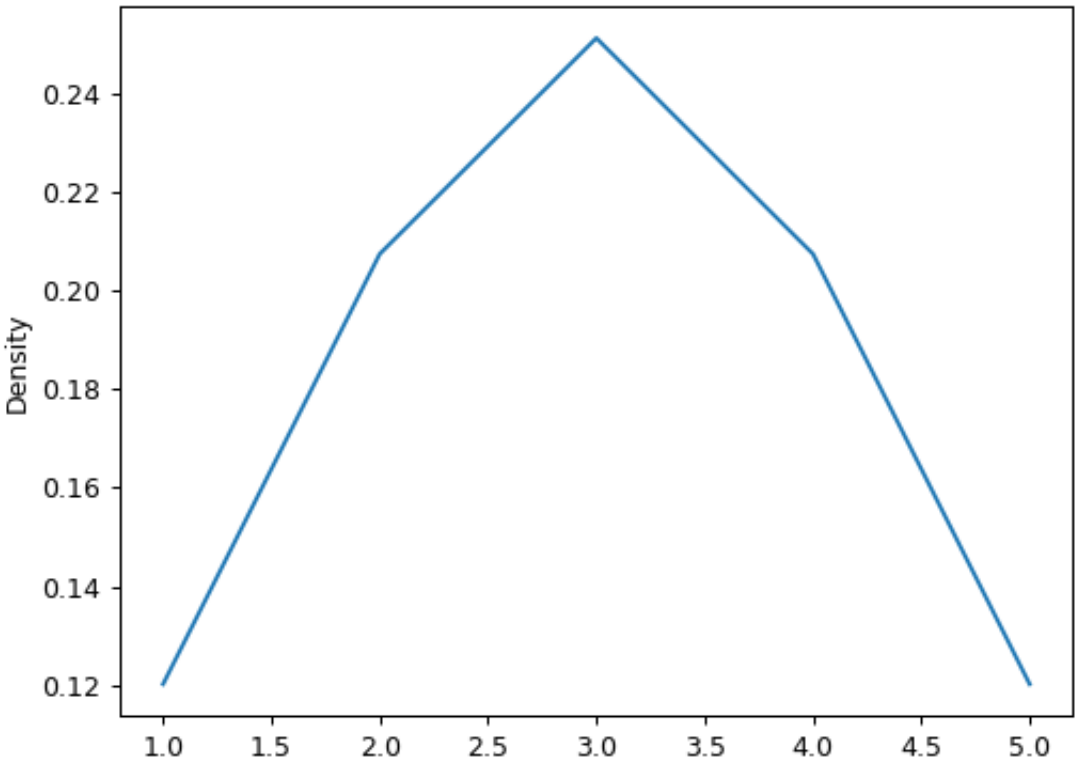
```
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:


Density
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7


Density
0.095
0.090
0.085
0.080
0.075
0.070
0.065
0.060
−1
0
1
2
3
4
5
6
7

```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```



For DataFrame, it works in the same way:

```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```

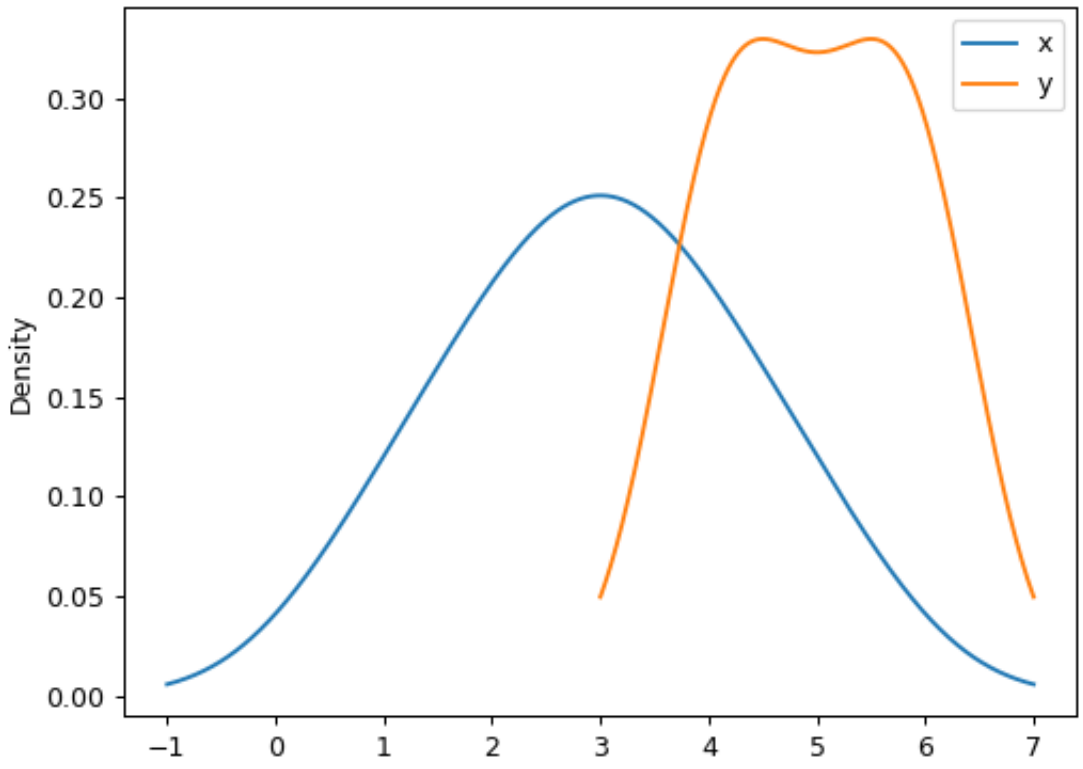
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

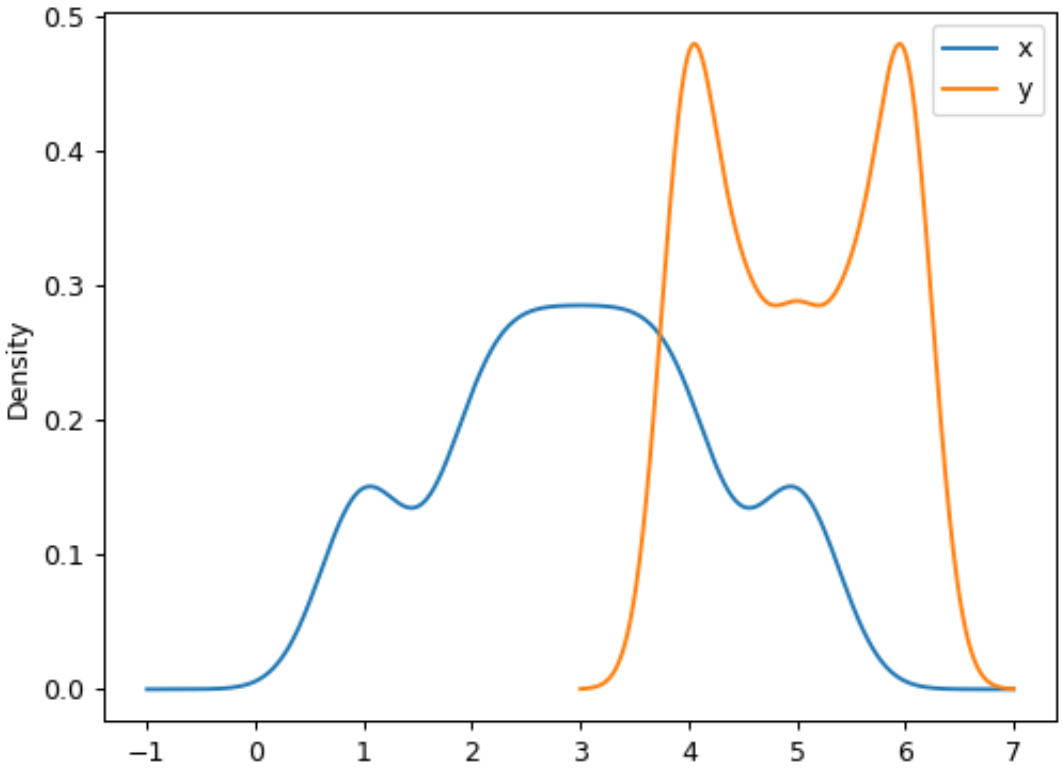
```
>>> ax = df.plot.kde(bw_method=0.3)
```

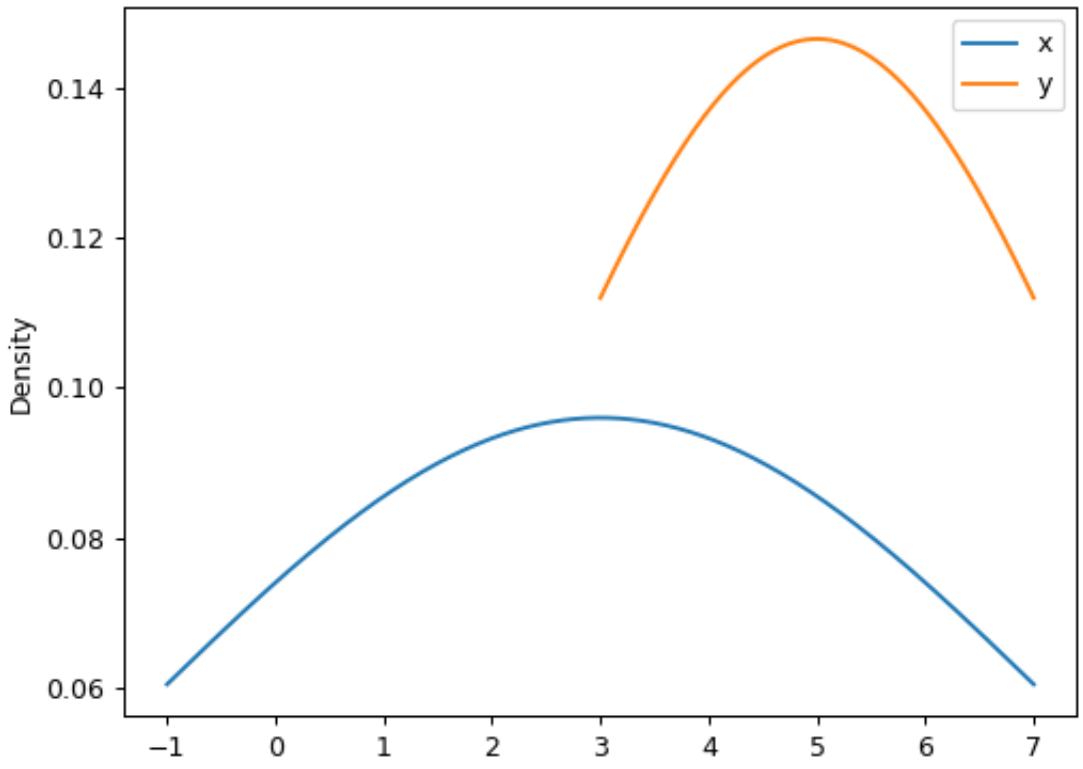
```
>>> ax = df.plot.kde(bw_method=3)
```

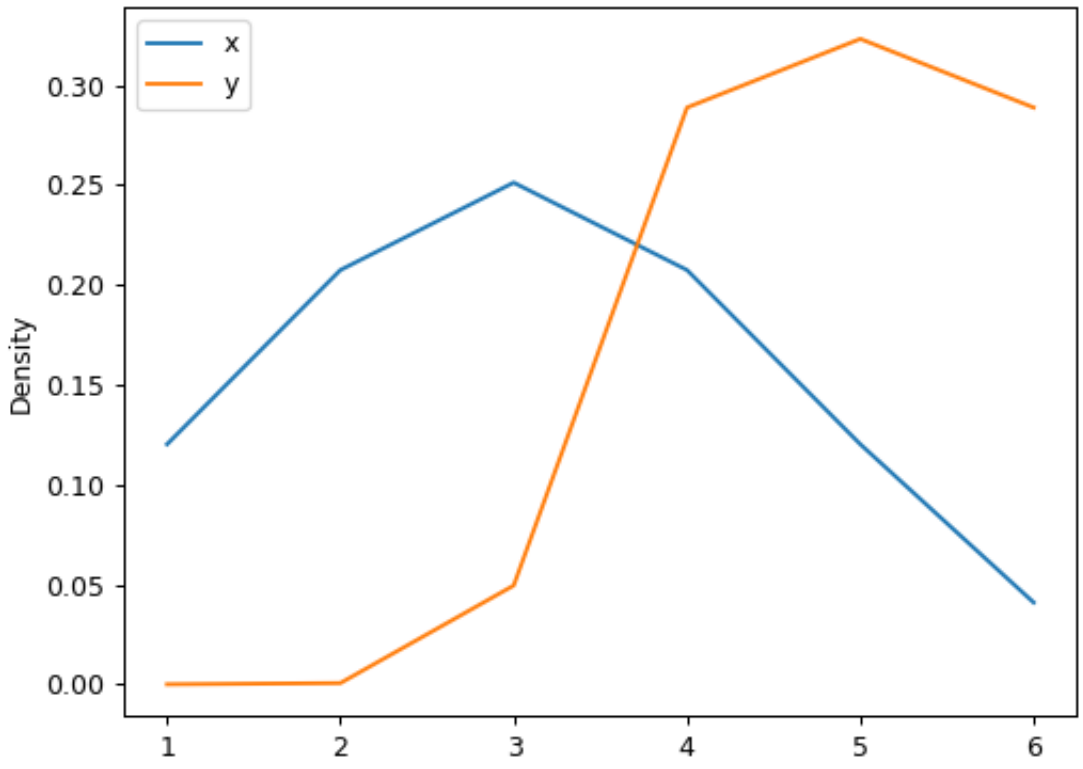
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```


x
y
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7


0.5
0.4
0.3
0.2
0.1
0.0
Density
−1
0
1
2
3
4
5
6
7
x
y


x
y
0.14
0.12
0.10
0.08
0.06
Density
−1
0
1
2
3
4
5
6
7


x
y
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
1
2
3
4
5
6

pandas.Series.plot.line

Series.plot.**line**(*x=None*, *y=None*, ***kwargs*)

Plot Series or DataFrame as lines.

This function is useful to plot lines using DataFrame's values as coordinates.

Parameters

x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

color [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:

- **A single color string referred to by name, RGB or RGBA code,** for instance 'red' or '#a98d19'.
- **A sequence of color strings referred to by name, RGB or RGBA** code, which will be used for each column recursively. For instance ['green','yellow'] each column's line will be filled in green or yellow, alternatively.
- **A dict of the form {column name** [color}, so that each column will be] colored accordingly. For example, if your columns are called *a* and *b*, then passing {'a': 'green', 'b': 'red'} will color lines for column *a* in green and lines for column *b* in red.

New in version 1.1.0.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one matplotlib.axes.Axes per column when subplots=True.

See also:

matplotlib.pyplot.plot Plot y versus x as lines and/or markers.

Examples

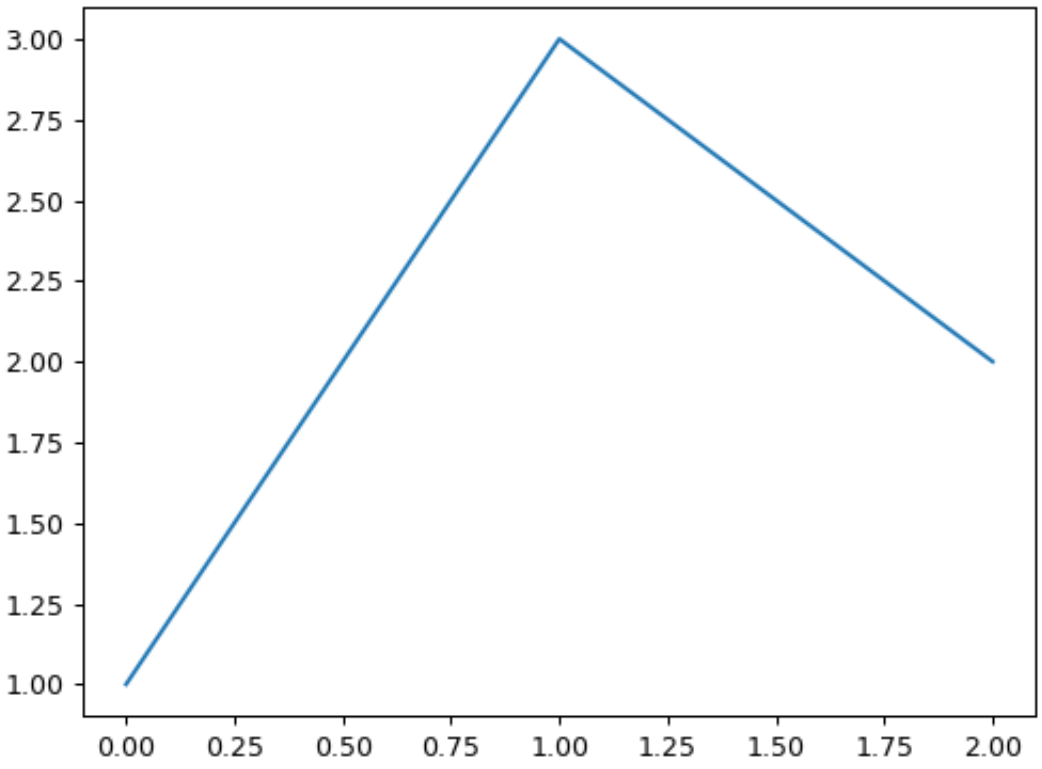
```
>>> s = pd.Series([1, 3, 2])
>>> s.plot.line()
```

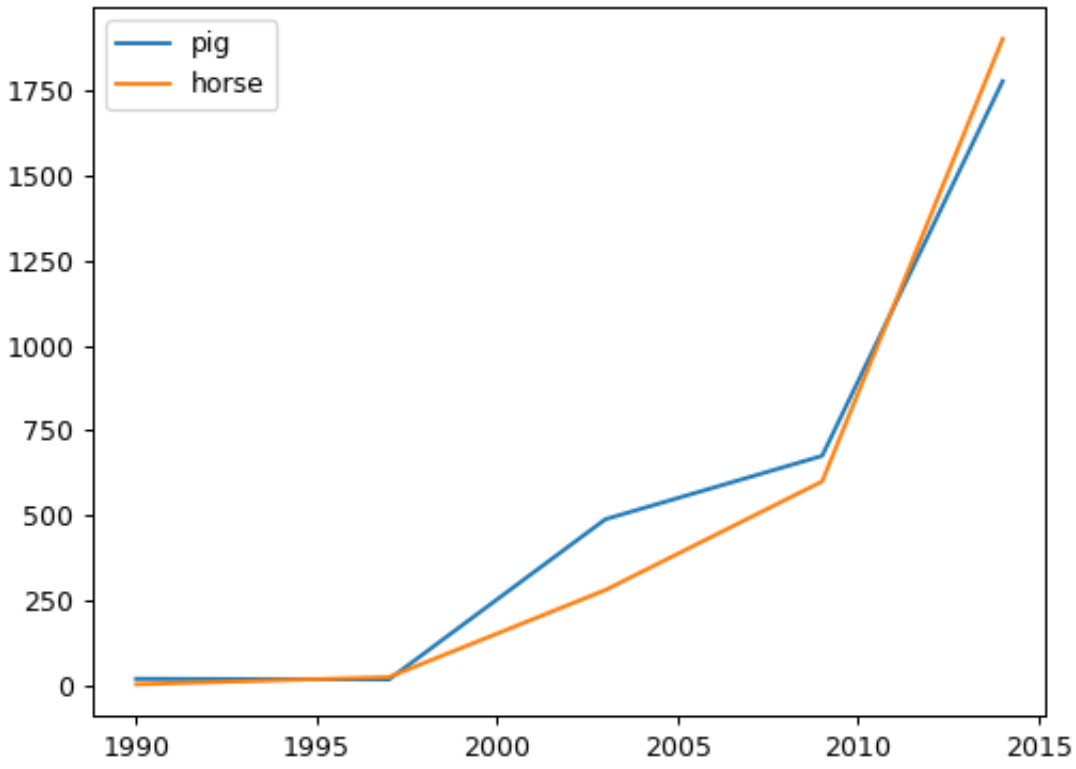
The following example shows the populations for some animals over the years.

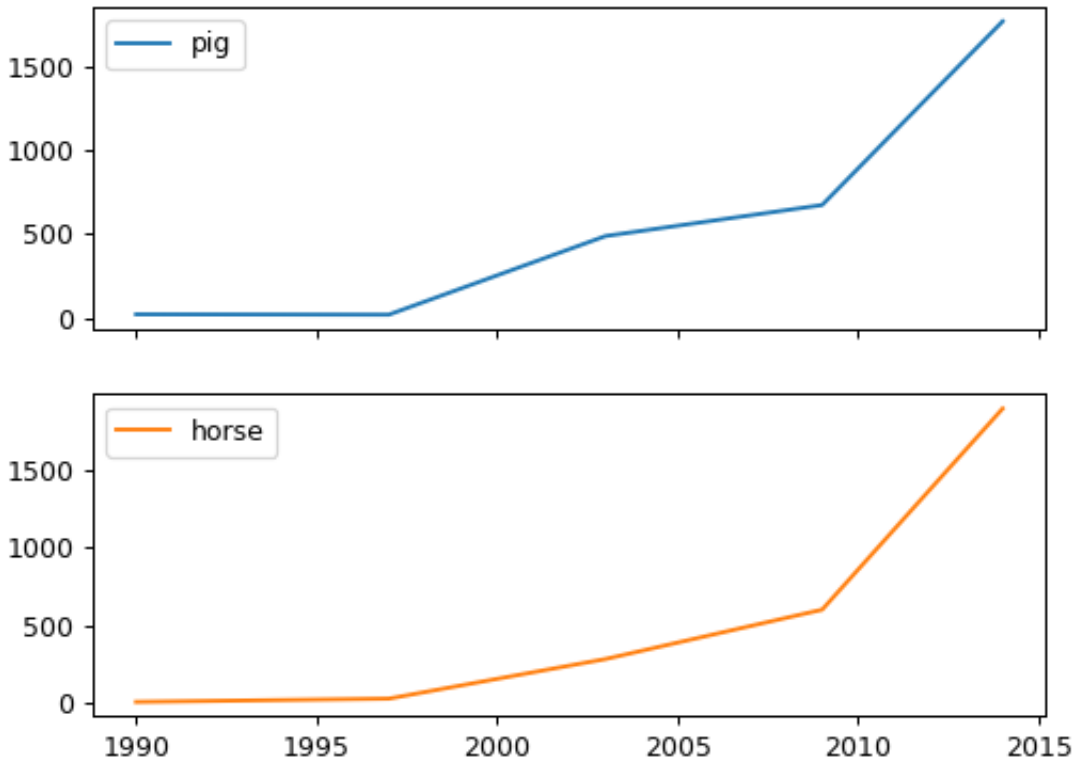
```
>>> df = pd.DataFrame({
...     'pig': [20, 18, 489, 675, 1776],
...     'horse': [4, 25, 281, 600, 1900]
...     }, index=[1990, 1997, 2003, 2009, 2014])
>>> lines = df.plot.line()
```

An example with subplots, so an array of axes is returned.

```
>>> axes = df.plot.line(subplots=True)
>>> type(axes)
<class 'numpy.ndarray'>
```

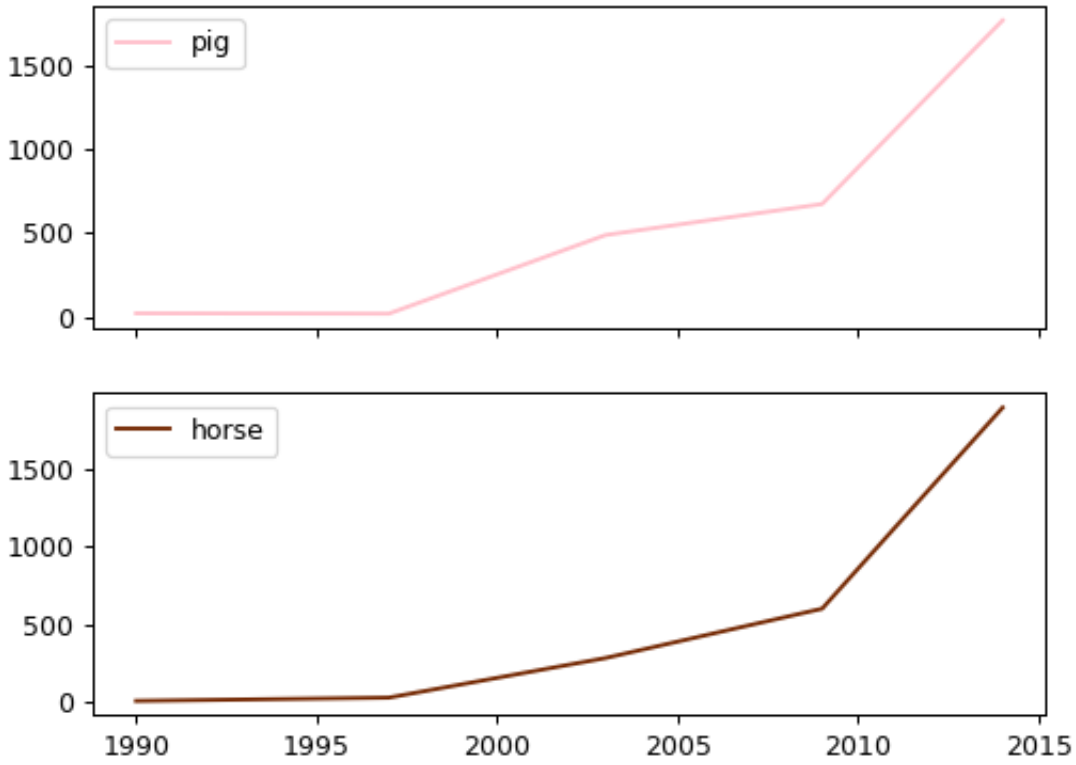

3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


pig
horse
1750
1500
1250
1000
750
500
250
0
1990
1995
2000
2005
2010
2015


pig
1500
1000
500
0
horse
1500
1000
500
0
1990
1995
2000
2005
2010
2015

Let's repeat the same example, but specifying colors for each column (in this case, for each animal).

```
>>> axes = df.plot.line(
...     subplots=True, color={"pig": "pink", "horse": "#742802"}
... )
```



The following example shows the relationship between both populations.

```
>>> lines = df.plot.line(x='pig', y='horse')
```

pandas.Series.plot.pie

`Series.plot.`**`pie`**`(**kwargs)`

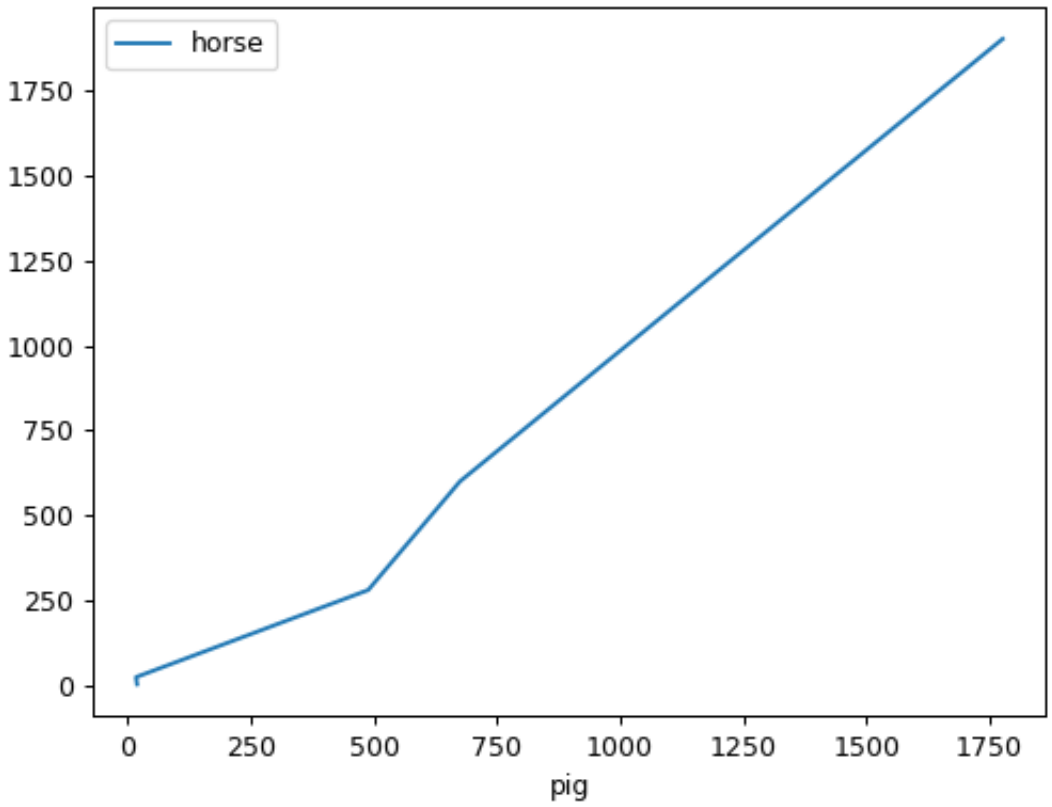
Generate a pie plot.

A pie plot is a proportional representation of the numerical data in a column. This function wraps `matplotlib.pyplot.pie()` for the specified column. If no column reference is passed and `subplots=True` a pie plot is drawn for each numerical column independently.

Parameters

y [int or label, optional] Label or position of the column to plot. If not provided, `subplots=True` argument must be passed.

****kwargs** Keyword arguments to pass on to *`DataFrame.plot()`*.


horse
1750
1500
1250
1000
750
500
250
0
0
250
500
750
1000
1250
1500
1750
pig

Returns

matplotlib.axes.Axes or np.ndarray of them A NumPy array is returned when *subplots* is True.

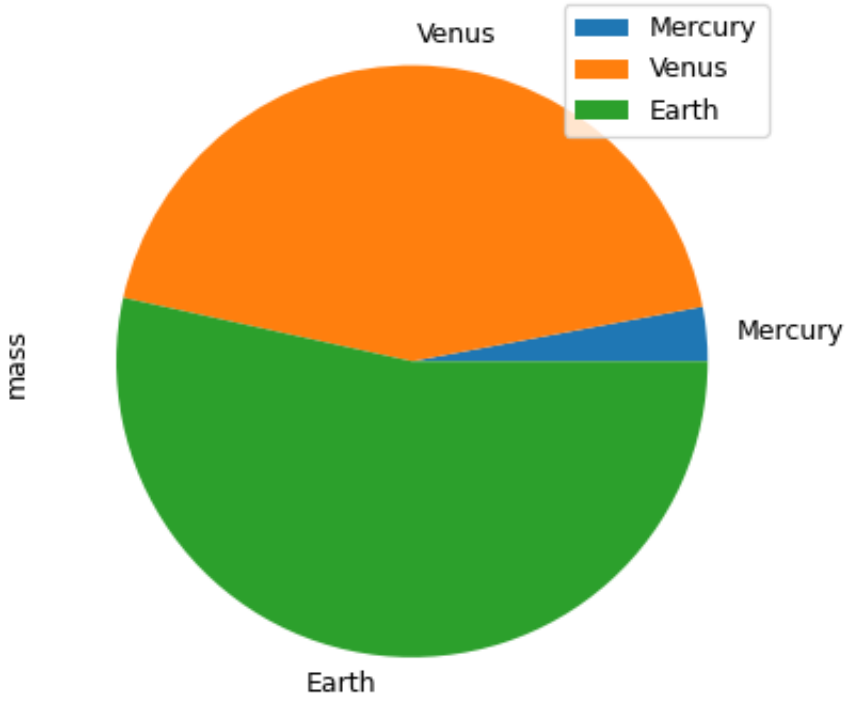
See also:

Series.plot.pie Generate a pie plot for a Series.
DataFrame.plot Make plots of a DataFrame.

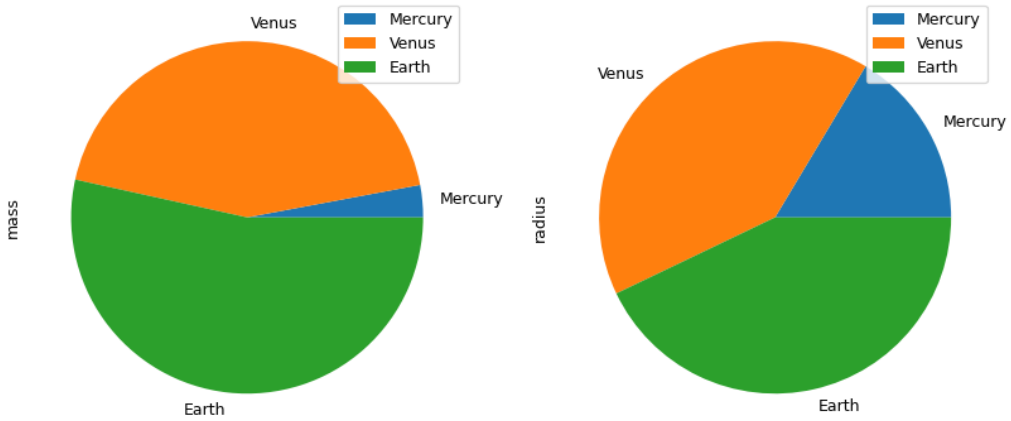
Examples

In the example below we have a DataFrame with the information about planet's mass and radius. We pass the 'mass' column to the pie function to get a pie plot.

```
>>> df = pd.DataFrame({'mass': [0.330, 4.87 , 5.97],
...                    'radius': [2439.7, 6051.8, 6378.1]},
...                   index=['Mercury', 'Venus', 'Earth'])
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
```




```
>>> plot = df.plot.pie(subplots=True, figsize=(11, 6))
```



Series.hist([by, ax, grid, xlabelsize, ...])	Draw histogram of the input series using matplotlib.

3.3.15 Serialization / IO / conversion

Series.to_pickle(path[, compression, ...])	Pickle (serialize) object to file.
Series.to_csv([path_or_buf, sep, na_rep, ...])	Write object to a comma-separated values (csv) file.
Series.to_dict([into])	Convert Series to {label -> value} dict or dict-like object.
Series.to_excel(excel_writer[, sheet_name, ...])	Write object to an Excel sheet.
Series.to_frame([name])	Convert Series to DataFrame.
Series.to_xarray()	Return an xarray object from the pandas object.
Series.to_hdf(path_or_buf, key[, mode, ...])	Write the contained data to an HDF5 file using HDFStore.
Series.to_sql(name, con[, schema, ...])	Write records stored in a DataFrame to a SQL database.
Series.to_json([path_or_buf, orient, ...])	Convert the object to a JSON string.
Series.to_string([buf, na_rep, ...])	Render a string representation of the Series.
Series.to_clipboard([excel, sep])	Copy object to the system clipboard.
Series.to_latex([buf, columns, col_space, ...])	Render object to a LaTeX tabular, longtable, or nested table/tabular.
Series.to_markdown([buf, mode, index, ...])	Print Series in Markdown-friendly format.

3.4 DataFrame

3.4.1 Constructor

DataFrame([data, index, columns, dtype, copy])	Two-dimensional, size-mutable, potentially heterogeneous tabular data.

pandas.DataFrame

class pandas.DataFrame(*data=None, index=None, columns=None, dtype=None, copy=False*)

dtype [dtype, default None] Data type to force. Only a single dtype is allowed. If None, infer.

copy [bool, default False] Copy data from inputs. Only affects DataFrame / 2d ndarray input.

See also:

DataFrame.from_records Constructor from tuples, also record arrays.
DataFrame.from_dict From dicts of Series, arrays, or dicts.
read_csv Read a comma-separated values (csv) file into DataFrame.
read_table Read general delimited file into DataFrame.
read_clipboard Read text from clipboard into DataFrame.

Examples

Constructing DataFrame from a dictionary.

```
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df
   col1  col2
0     1     3
1     2     4
```

Notice that the inferred dtype is int64.

```
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```

To enforce a single dtype:

```
>>> df = pd.DataFrame(data=d, dtype=np.int8)
>>> df.dtypes
col1    int8
col2    int8
dtype: object
```

Constructing DataFrame from numpy ndarray:

```
>>> df2 = pd.DataFrame(np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]]),
...                    columns=['a', 'b', 'c'])
>>> df2
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

Constructing DataFrame from dataclass:

```
>>> from dataclasses import make_dataclass
>>> Point = make_dataclass("Point", [("x", int), ("y", int)])
>>> pd.DataFrame([Point(0, 0), Point(0, 3), Point(2, 3)])
   x  y
0  0  0
1  0  3
2  2  3
```

Attributes

at	Access a single value for a row/column label pair.
attrs	Dictionary of global attributes of this dataset.
axes	Return a list representing the axes of the DataFrame.
columns	The column labels of the DataFrame.
dtypes	Return the dtypes in the DataFrame.
empty	Indicator whether DataFrame is empty.
flags	Get the properties associated with this pandas object.
iat	Access a single value for a row/column pair by integer position.
iloc	Purely integer-location based indexing for selection by position.
index	The index (row labels) of the DataFrame.
loc	Access a group of rows and columns by label(s) or a boolean array.
ndim	Return an int representing the number of axes / array dimensions.
shape	Return a tuple representing the dimensionality of the DataFrame.
size	Return an int representing the number of elements in this object.
style	Returns a Styler object.
values	Return a Numpy representation of the DataFrame.

pandas.DataFrame.at

property DataFrame.**at**

Access a single value for a row/column label pair.

Similar to `loc`, in that both provide label-based lookups. Use `at` if you only need to get or set a single value in a DataFrame or Series.

Raises

KeyError If 'label' does not exist in DataFrame.

See also:

DataFrame.iat Access a single value for a row/column pair by integer position.

DataFrame.loc Access a group of rows and columns by label(s).

Series.at Access a single value using a label.

Examples

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                   index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
    A   B   C
4   0   2   3
5   0   4   1
6  10  20  30
```

Get value at specified row/column pair

```
>>> df.at[4, 'B']
2
```

Set value at specified row/column pair

```
>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```

Get value within a Series

```
>>> df.loc[5].at['B']
4
```

pandas.DataFrame.attrs

property DataFrame.**attrs**

Dictionary of global attributes of this dataset.

> **Warning:** attrs is experimental and may change without warning.

See also:

DataFrame.flags Global flags applying to this object.

pandas.DataFrame.axes

property DataFrame.**axes**

Return a list representing the axes of the DataFrame.

It has the row axis labels and column axis labels as the only members. They are returned in that order.

Examples

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.axes
[RangeIndex(start=0, stop=2, step=1), Index(['col1', 'col2'],
dtype='object')]
```

pandas.DataFrame.columns

DataFrame.**columns**: *Index*

The column labels of the DataFrame.

pandas.DataFrame.dtypes

property DataFrame.**dtypes**

Return the dtypes in the DataFrame.

This returns a Series with the data type of each column. The result's index is the original DataFrame's columns. Columns with mixed types are stored with the `object` dtype. See *the User Guide* for more.

Returns

pandas.Series The data type of each column.

Examples

```
>>> df = pd.DataFrame({'float': [1.0],
...                    'int': [1],
...                    'datetime': [pd.Timestamp('20180310')],
...                    'string': ['foo']})
>>> df.dtypes
float              float64
int                  int64
datetime    datetime64[ns]
string              object
dtype: object
```

pandas.DataFrame.empty

property DataFrame.**empty**

Indicator whether DataFrame is empty.

True if DataFrame is entirely empty (no items), meaning any of the axes are of length 0.

Returns

bool If DataFrame is empty, return True, if not return False.

See also:

Series.dropna Return series without null values.

DataFrame.dropna Return DataFrame with labels on given axis omitted where (all or any) data are missing.

Notes

If DataFrame contains only NaNs, it is still not considered empty. See the example below.

Examples

An example of an actual empty DataFrame. Notice the index is empty:

```
>>> df_empty = pd.DataFrame({'A' : []})
>>> df_empty
Empty DataFrame
Columns: [A]
Index: []
>>> df_empty.empty
True
```

If we only have NaNs in our DataFrame, it is not considered empty! We will need to drop the NaNs to make the DataFrame empty:

```
>>> df = pd.DataFrame({'A' : [np.nan]})
>>> df
    A
0 NaN
>>> df.empty
False
>>> df.dropna().empty
True
```

pandas.DataFrame.flags

property DataFrame.**flags**

Get the properties associated with this pandas object.

The available flags are

- *Flags.allows_duplicate_labels*

See also:

Flags Flags that apply to pandas objects.

DataFrame.attrs Global metadata applying to this dataset.

Notes

"Flags" differ from "metadata". Flags reflect properties of the pandas object (the Series or DataFrame). Metadata refer to properties of the dataset, and should be stored in *DataFrame.attrs*.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2]})
>>> df.flags
<Flags(allows_duplicate_labels=True)>
```

Flags can be get or set using `.`

```
>>> df.flags.allows_duplicate_labels
True
>>> df.flags.allows_duplicate_labels = False
```

Or by slicing with a key

```
>>> df.flags["allows_duplicate_labels"]
False
>>> df.flags["allows_duplicate_labels"] = True
```

pandas.DataFrame.iat

property DataFrame.**iat**

Access a single value for a row/column pair by integer position.

Similar to `iloc`, in that both provide integer-based lookups. Use `iat` if you only need to get or set a single value in a DataFrame or Series.

Raises

IndexError When integer position is out of bounds.

See also:

DataFrame.at Access a single value for a row/column label pair.

DataFrame.loc Access a group of rows and columns by label(s).

DataFrame.iloc Access a group of rows and columns by integer position(s).

Examples

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                   columns=['A', 'B', 'C'])
>>> df
    A   B   C
0   0   2   3
1   0   4   1
2  10  20  30
```

Get value at specified row/column pair

```
>>> df.iat[1, 2]
1
```

Set value at specified row/column pair

```
>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
```

Get value within a series

```
>>> df.loc[0].iat[1]
2
```

pandas.DataFrame.iloc

property DataFrame.**iloc**

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from `0` to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. `5`.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.
- A `callable` function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above). This is useful in method chains, when you don't have a reference to the calling object, but would like to base your selection on some value.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at *Selection by Position*.

See also:

DataFrame.iat Fast integer location scalar accessor.

DataFrame.loc Purely label-location based indexer for selection by label.

Series.iloc Purely integer-location based indexing for selection by position.

Examples

```
>>> mydict = [{'a': 1, 'b': 2, 'c': 3, 'd': 4},
...           {'a': 100, 'b': 200, 'c': 300, 'd': 400},
...           {'a': 1000, 'b': 2000, 'c': 3000, 'd': 4000 }]
>>> df = pd.DataFrame(mydict)
>>> df
      a     b     c     d
0     1     2     3     4
1   100   200   300   400
2  1000  2000  3000  4000
```

Indexing just the rows

With a scalar integer.

```
>>> type(df.iloc[0])
<class 'pandas.core.series.Series'>
>>> df.iloc[0]
a    1
b    2
c    3
d    4
Name: 0, dtype: int64
```

With a list of integers.

```
>>> df.iloc[[0]]
   a  b  c  d
0  1  2  3  4
>>> type(df.iloc[[0]])
<class 'pandas.core.frame.DataFrame'>
```

```
>>> df.iloc[[0, 1]]
     a    b    c    d
0    1    2    3    4
1  100  200  300  400
```

With a *slice* object.

```
>>> df.iloc[:3]
      a     b     c     d
0     1     2     3     4
1   100   200   300   400
2  1000  2000  3000  4000
```

With a boolean mask the same length as the index.

```
>>> df.iloc[[True, False, True]]
      a     b     c     d
0     1     2     3     4
2  1000  2000  3000  4000
```

With a callable, useful in method chains. The *x* passed to the `lambda` is the DataFrame being sliced. This selects the rows whose index label even.

```
>>> df.iloc[lambda x: x.index % 2 == 0]
      a     b     c     d
0     1     2     3     4
2  1000  2000  3000  4000
```

Indexing both axes

You can mix the indexer types for the index and columns. Use `:` to select the entire axis.

With scalar integers.

```
>>> df.iloc[0, 1]
2
```

With lists of integers.

```
>>> df.iloc[[0, 2], [1, 3]]
      b     d
0     2     4
2  2000  4000
```

With *slice* objects.

```
>>> df.iloc[1:3, 0:3]
      a     b     c
1   100   200   300
2  1000  2000  3000
```

With a boolean array whose length matches the columns.

```
>>> df.iloc[:, [True, False, True, False]]
      a     c
0     1     3
1   100   300
2  1000  3000
```

With a callable function that expects the Series or DataFrame.

```
>>> df.iloc[:, lambda df: [0, 2]]
      a     c
0     1     3
1   100   300
2  1000  3000
```

pandas.DataFrame.index

DataFrame.**index**: *Index*

The index (row labels) of the DataFrame.

pandas.DataFrame.loc

property DataFrame.**loc**

Access a group of rows and columns by label(s) or a boolean array.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'`.

  Warning: Note that contrary to usual python slices, **both** the start and the stop are included

- A boolean array of the same length as the axis being sliced, e.g. `[True, False, True]`.
- An alignable boolean Series. The index of the key will be aligned before masking.

- An alignable Index. The Index of the returned selection will be the input.
- A `callable` function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above)

See more at *Selection by Label*.

Raises

KeyError If any items are not found.

IndexingError If an indexed key is passed and its index is unalignable to the frame index.

See also:

DataFrame.at Access a single value for a row/column label pair.

DataFrame.iloc Access group of rows and columns by integer position(s).

DataFrame.xs Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

Series.loc Access group of values using labels.

Examples

Getting values

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...       index=['cobra', 'viper', 'sidewinder'],
...       columns=['max_speed', 'shield'])
>>> df
            max_speed  shield
cobra               1       2
viper               4       5
sidewinder          7       8
```

Single label. Note this returns the row as a Series.

```
>>> df.loc['viper']
max_speed    4
shield       5
Name: viper, dtype: int64
```

List of labels. Note using `[[]]` returns a DataFrame.

```
>>> df.loc[['viper', 'sidewinder']]
            max_speed  shield
viper               4       5
sidewinder          7       8
```

Single label for row and column

```
>>> df.loc['cobra', 'shield']
2
```

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc['cobra':'viper', 'max_speed']
cobra    1
viper    4
Name: max_speed, dtype: int64
```

Boolean list with the same length as the row axis

```
>>> df.loc[[False, False, True]]
            max_speed  shield
sidewinder          7       8
```

Alignable boolean Series:

```
>>> df.loc[pd.Series([False, True, False],
...         index=['viper', 'sidewinder', 'cobra'])]
            max_speed  shield
sidewinder          7       8
```

Index (same behavior as `df.reindex`)

```
>>> df.loc[pd.Index(["cobra", "viper"], name="foo")]
       max_speed  shield
foo
cobra          1       2
viper          4       5
```

Conditional that returns a boolean Series

```
>>> df.loc[df['shield'] > 6]
            max_speed  shield
sidewinder          7       8
```

Conditional that returns a boolean Series with column labels specified

```
>>> df.loc[df['shield'] > 6, ['max_speed']]
            max_speed
sidewinder          7
```

Callable that returns a boolean Series

```
>>> df.loc[lambda df: df['shield'] == 8]
            max_speed  shield
sidewinder          7       8
```

Setting values

Set value for all items matching the list of labels

```
>>> df.loc[['viper', 'sidewinder'], ['shield']] = 50
>>> df
            max_speed  shield
cobra               1       2
viper               4      50
sidewinder          7      50
```

Set value for an entire row

```
>>> df.loc['cobra'] = 10
>>> df
            max_speed  shield
cobra              10      10
viper               4      50
sidewinder          7      50
```

Set value for an entire column

```
>>> df.loc[:, 'max_speed'] = 30
>>> df
            max_speed  shield
cobra              30      10
viper              30      50
sidewinder         30      50
```

Set value for rows matching callable condition

```
>>> df.loc[df['shield'] > 35] = 0
>>> df
            max_speed  shield
cobra              30      10
viper               0       0
sidewinder          0       0
```

Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...      index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
   max_speed  shield
7          1       2
8          4       5
9          7       8
```

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc[7:9]
   max_speed  shield
7          1       2
8          4       5
9          7       8
```

Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

```
>>> tuples = [
...     ('cobra', 'mark i'), ('cobra', 'mark ii'),
...     ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
...     ('viper', 'mark ii'), ('viper', 'mark iii')
... ]
>>> index = pd.MultiIndex.from_tuples(tuples)
>>> values = [[12, 2], [0, 4], [10, 20],
...           [1, 4], [7, 1], [16, 36]]
```

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```
>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
                     max_speed  shield
cobra      mark i            12       2
           mark ii            0       4
sidewinder mark i            10      20
           mark ii            1       4
viper      mark ii            7       1
           mark iii          16      36
```

Single label. Note this returns a DataFrame with a single index.

```
>>> df.loc['cobra']
         max_speed  shield
mark i          12       2
mark ii          0       4
```

Single index tuple. Note this returns a Series.

```
>>> df.loc[('cobra', 'mark ii')]
max_speed    0
shield       4
Name: (cobra, mark ii), dtype: int64
```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```
>>> df.loc['cobra', 'mark i']
max_speed    12
shield        2
Name: (cobra, mark i), dtype: int64
```

Single tuple. Note using `[[]]` returns a DataFrame.

```
>>> df.loc[[('cobra', 'mark ii')]]
               max_speed  shield
cobra mark ii          0       4
```

Single tuple for the index with a single label for the column

```
>>> df.loc[('cobra', 'mark i'), 'shield']
2
```

Slice from index tuple to single label

```
>>> df.loc[('cobra', 'mark i'):'viper']
                     max_speed  shield
cobra      mark i            12       2
           mark ii            0       4
sidewinder mark i            10      20
           mark ii            1       4
viper      mark ii            7       1
           mark iii          16      36
```

Slice from index tuple to index tuple

```
>>> df.loc[('cobra', 'mark i'):('viper', 'mark ii')]
                     max_speed  shield
cobra      mark i           12       2
           mark ii           0       4
sidewinder mark i           10      20
           mark ii           1       4
viper      mark ii           7       1
```

pandas.DataFrame.ndim

property DataFrame.**ndim**

Return an int representing the number of axes / array dimensions.

Return 1 if Series. Otherwise return 2 if DataFrame.

See also:

ndarray.ndim Number of array dimensions.

Examples

```
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.ndim
1
```

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.ndim
2
```

pandas.DataFrame.shape

property DataFrame.**shape**

Return a tuple representing the dimensionality of the DataFrame.

See also:

ndarray.shape Tuple of array dimensions.

Examples

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.shape
(2, 2)
```

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4],
...                    'col3': [5, 6]})
>>> df.shape
(2, 3)
```

pandas.DataFrame.size

property DataFrame.**size**

Return an int representing the number of elements in this object.

Return the number of rows if Series. Otherwise return the number of rows times number of columns if DataFrame.

See also:

ndarray.size Number of elements in the array.

Examples

```
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.size
3
```

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.size
4
```

pandas.DataFrame.style

property DataFrame.**style**

Returns a Styler object.

Contains methods for building a styled HTML representation of the DataFrame.

See also:

io.formats.style.Styler Helps style a DataFrame or Series according to the data with HTML and CSS.

pandas.DataFrame.values

property DataFrame.**values**

Return a Numpy representation of the DataFrame.

Warning: We recommend using *DataFrame.to_numpy()* instead.

Only the values in the DataFrame will be returned, the axes labels will be removed.

Returns

numpy.ndarray The values of the DataFrame.

See also:

DataFrame.to_numpy Recommended alternative to this method.

DataFrame.index Retrieve the index labels.

DataFrame.columns Retrieving the column names.

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcast to int32. By `numpy.find_common_type()` convention, mixing int64 and uint64 will result in a float64 dtype.

Examples

A DataFrame where all columns are the same type (e.g., int64) results in an array of the same type.

```
>>> df = pd.DataFrame({'age':    [ 3,  29],
...                    'height': [94, 170],
...                    'weight': [31, 115]})
>>> df
   age  height  weight
0    3      94      31
1   29     170     115
>>> df.dtypes
age       int64
height    int64
weight    int64
dtype: object
>>> df.values
array([[  3,  94,  31],
       [ 29, 170, 115]])
```

A DataFrame with mixed type columns(e.g., str/object, int64, float32) results in an ndarray of the broadest type that accommodates these mixed types (e.g., object).

```
>>> df2 = pd.DataFrame([('parrot',   24.0, 'second'),
...                     ('lion',     80.5, 1),
...                     ('monkey', np.nan, None)],
...                    columns=('name', 'max_speed', 'rank'))
>>> df2.dtypes
name          object
max_speed    float64
rank          object
dtype: object
>>> df2.values
array([['parrot', 24.0, 'second'],
       ['lion', 80.5, 1],
       ['monkey', nan, None]], dtype=object)
```

Methods

abs()	Return a Series/DataFrame with absolute numeric value of each element.
add(other[, axis, level, fill_value])	Get Addition of dataframe and other, element-wise (binary operator *add*).
add_prefix(prefix)	Prefix labels with string *prefix*.
add_suffix(suffix)	Suffix labels with string *suffix*.
agg([func, axis])	Aggregate using one or more operations over the specified axis.
aggregate([func, axis])	Aggregate using one or more operations over the specified axis.
align(other[, join, axis, level, copy, ...])	Align two objects on their axes with the specified join method.
all([axis, bool_only, skipna, level])	Return whether all elements are True, potentially over an axis.
any([axis, bool_only, skipna, level])	Return whether any element is True, potentially over an axis.
append(other[, ignore_index, ...])	Append rows of *other* to the end of caller, returning a new object.
apply(func[, axis, raw, result_type, args])	Apply a function along an axis of the DataFrame.
applymap(func[, na_action])	Apply a function to a Dataframe elementwise.
asfreq(freq[, method, how, normalize, ...])	Convert TimeSeries to specified frequency.
asof(where[, subset])	Return the last row(s) without any NaNs before *where*.
assign(**kwargs)	Assign new columns to a DataFrame.
astype(dtype[, copy, errors])	Cast a pandas object to a specified dtype `dtype`.
at_time(time[, asof, axis])	Select values at particular time of day (e.g., 9:30AM).
backfill([axis, inplace, limit, downcast])	Synonym for *DataFrame.fillna()* with `method='bfill'`.
between_time(start_time, end_time[, ...])	Select values between particular times of the day (e.g., 9:00-9:30 AM).
bfill([axis, inplace, limit, downcast])	Synonym for *DataFrame.fillna()* with `method='bfill'`.
bool()	Return the bool of a single element Series or DataFrame.
boxplot([column, by, ax, fontsize, rot, ...])	Make a box plot from DataFrame columns.
clip([lower, upper, axis, inplace])	Trim values at input threshold(s).
combine(other, func[, fill_value, overwrite])	Perform column-wise combine with another DataFrame.
combine_first(other)	Update null elements with value in the same location in *other*.
compare(other[, align_axis, keep_shape, ...])	Compare to another DataFrame and show the differences.
convert_dtypes([infer_objects, ...])	Convert columns to best possible dtypes using dtypes supporting `pd.NA`.
copy([deep])	Make a copy of this object's indices and data.
corr([method, min_periods])	Compute pairwise correlation of columns, excluding NA/null values.
corrwith(other[, axis, drop, method])	Compute pairwise correlation.

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count([axis, level, numeric_only])	Count non-NA cells for each column or row.
cov([min_periods, ddof])	Compute pairwise covariance of columns, excluding NA/null values.
cummax([axis, skipna])	Return cumulative maximum over a DataFrame or Series axis.
cummin([axis, skipna])	Return cumulative minimum over a DataFrame or Series axis.
cumprod([axis, skipna])	Return cumulative product over a DataFrame or Series axis.
cumsum([axis, skipna])	Return cumulative sum over a DataFrame or Series axis.
describe([percentiles, include, exclude, ...])	Generate descriptive statistics.
diff([periods, axis])	First discrete difference of element.
div(other[, axis, level, fill_value])	Get Floating division of dataframe and other, element-wise (binary operator *truediv*).
divide(other[, axis, level, fill_value])	Get Floating division of dataframe and other, element-wise (binary operator *truediv*).
dot(other)	Compute the matrix multiplication between the DataFrame and other.
drop([labels, axis, index, columns, level, ...])	Drop specified labels from rows or columns.
drop_duplicates([subset, keep, inplace, ...])	Return DataFrame with duplicate rows removed.
droplevel(level[, axis])	Return DataFrame with requested index / column level(s) removed.
dropna([axis, how, thresh, subset, inplace])	Remove missing values.
duplicated([subset, keep])	Return boolean Series denoting duplicate rows.
eq(other[, axis, level])	Get Equal to of dataframe and other, element-wise (binary operator *eq*).
equals(other)	Test whether two objects contain the same elements.
eval(expr[, inplace])	Evaluate a string describing operations on DataFrame columns.
ewm([com, span, halflife, alpha, ...])	Provide exponential weighted (EW) functions.
expanding([min_periods, center, axis])	Provide expanding transformations.
explode(column[, ignore_index])	Transform each element of a list-like to a row, replicating index values.
ffill([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='ffill'.
fillna([value, method, axis, inplace, ...])	Fill NA/NaN values using the specified method.
filter([items, like, regex, axis])	Subset the dataframe rows or columns according to the specified index labels.
first(offset)	Select initial periods of time series data based on a date offset.
first_valid_index()	Return index for first non-NA/null value.
floordiv(other[, axis, level, fill_value])	Get Integer division of dataframe and other, element-wise (binary operator *floordiv*).
from_dict(data[, orient, dtype, columns])	Construct DataFrame from dict of array-like or dicts.
from_records(data[, index, exclude, ...])	Convert structured or record ndarray to DataFrame.
ge(other[, axis, level])	Get Greater than or equal to of dataframe and other, element-wise (binary operator *ge*).
get(key[, default])	Get item from object for given key (ex: DataFrame column).

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groupby([by, axis, level, as_index, sort, ...])	Group DataFrame using a mapper or by a Series of columns.
gt(other[, axis, level])	Get Greater than of dataframe and other, element-wise (binary operator *gt*).
head([n])	Return the first *n* rows.
hist([column, by, grid, xlabelsize, xrot, ...])	Make a histogram of the DataFrame's.
idxmax([axis, skipna])	Return index of first occurrence of maximum over requested axis.
idxmin([axis, skipna])	Return index of first occurrence of minimum over requested axis.
infer_objects()	Attempt to infer better dtypes for object columns.
info([verbose, buf, max_cols, memory_usage, ...])	Print a concise summary of a DataFrame.
insert(loc, column, value[, allow_duplicates])	Insert column into DataFrame at specified location.
interpolate([method, axis, limit, inplace, ...])	Fill NaN values using an interpolation method.
isin(values)	Whether each element in the DataFrame is contained in values.
isna()	Detect missing values.
isnull()	Detect missing values.
items()	Iterate over (column name, Series) pairs.
iteritems()	Iterate over (column name, Series) pairs.
iterrows()	Iterate over DataFrame rows as (index, Series) pairs.
itertuples([index, name])	Iterate over DataFrame rows as namedtuples.
join(other[, on, how, lsuffix, rsuffix, sort])	Join columns of another DataFrame.
keys()	Get the 'info axis' (see Indexing for more).
kurt([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis.
kurtosis([axis, skipna, level, numeric_only])	Return unbiased kurtosis over requested axis.
last(offset)	Select final periods of time series data based on a date offset.
last_valid_index()	Return index for last non-NA/null value.
le(other[, axis, level])	Get Less than or equal to of dataframe and other, element-wise (binary operator *le*).
lookup(row_labels, col_labels)	(DEPRECATED) Label-based "fancy indexing" function for DataFrame.
lt(other[, axis, level])	Get Less than of dataframe and other, element-wise (binary operator *lt*).
mad([axis, skipna, level])	Return the mean absolute deviation of the values over the requested axis.
mask(cond[, other, inplace, axis, level, ...])	Replace values where the condition is True.
max([axis, skipna, level, numeric_only])	Return the maximum of the values over the requested axis.
mean([axis, skipna, level, numeric_only])	Return the mean of the values over the requested axis.
median([axis, skipna, level, numeric_only])	Return the median of the values over the requested axis.
melt([id_vars, value_vars, var_name, ...])	Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.
memory_usage([index, deep])	Return the memory usage of each column in bytes.
merge(right[, how, on, left_on, right_on, ...])	Merge DataFrame or named Series objects with a database-style join.

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min([axis, skipna, level, numeric_only])	Return the minimum of the values over the requested axis.
mod(other[, axis, level, fill_value])	Get Modulo of dataframe and other, element-wise (binary operator *mod*).
mode([axis, numeric_only, dropna])	Get the mode(s) of each element along the selected axis.
mul(other[, axis, level, fill_value])	Get Multiplication of dataframe and other, element-wise (binary operator *mul*).
multiply(other[, axis, level, fill_value])	Get Multiplication of dataframe and other, element-wise (binary operator *mul*).
ne(other[, axis, level])	Get Not equal to of dataframe and other, element-wise (binary operator *ne*).
nlargest(n, columns[, keep])	Return the first *n* rows ordered by *columns* in descending order.
notna()	Detect existing (non-missing) values.
notnull()	Detect existing (non-missing) values.
nsmallest(n, columns[, keep])	Return the first *n* rows ordered by *columns* in ascending order.
nunique([axis, dropna])	Count distinct observations over requested axis.
pad([axis, inplace, limit, downcast])	Synonym for *DataFrame.fillna()* with `method='ffill'`.
pct_change([periods, fill_method, limit, freq])	Percentage change between the current and a prior element.
pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs).
pivot([index, columns, values])	Return reshaped DataFrame organized by given index / column values.
pivot_table([values, index, columns, ...])	Create a spreadsheet-style pivot table as a DataFrame.
plot	alias of `pandas.plotting._core.PlotAccessor`
pop(item)	Return item and drop from frame.
pow(other[, axis, level, fill_value])	Get Exponential power of dataframe and other, element-wise (binary operator *pow*).
prod([axis, skipna, level, numeric_only, ...])	Return the product of the values over the requested axis.
product([axis, skipna, level, numeric_only, ...])	Return the product of the values over the requested axis.
quantile([q, axis, numeric_only, interpolation])	Return values at the given quantile over requested axis.
query(expr[, inplace])	Query the columns of a DataFrame with a boolean expression.
radd(other[, axis, level, fill_value])	Get Addition of dataframe and other, element-wise (binary operator *radd*).
rank([axis, method, numeric_only, ...])	Compute numerical data ranks (1 through n) along axis.
rdiv(other[, axis, level, fill_value])	Get Floating division of dataframe and other, element-wise (binary operator *rtruediv*).
reindex([labels, index, columns, axis, ...])	Conform Series/DataFrame to new index with optional filling logic.
reindex_like(other[, method, copy, limit, ...])	Return an object with matching indices as other object.

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rename([mapper, index, columns, axis, copy, ...])	Alter axes labels.
rename_axis([mapper, index, columns, axis, ...])	Set the name of the axis for the index or columns.
reorder_levels(order[, axis])	Rearrange index levels using input order.
replace([to_replace, value, inplace, limit, ...])	Replace values given in *to_replace* with *value*.
resample(rule[, axis, closed, label, ...])	Resample time-series data.
reset_index([level, drop, inplace, ...])	Reset the index, or a level of it.
rfloordiv(other[, axis, level, fill_value])	Get Integer division of dataframe and other, element-wise (binary operator *rfloordiv*).
rmod(other[, axis, level, fill_value])	Get Modulo of dataframe and other, element-wise (binary operator *rmod*).
rmul(other[, axis, level, fill_value])	Get Multiplication of dataframe and other, element-wise (binary operator *rmul*).
rolling(window[, min_periods, center, ...])	Provide rolling window calculations.
round([decimals])	Round a DataFrame to a variable number of decimal places.
rpow(other[, axis, level, fill_value])	Get Exponential power of dataframe and other, element-wise (binary operator *rpow*).
rsub(other[, axis, level, fill_value])	Get Subtraction of dataframe and other, element-wise (binary operator *rsub*).
rtruediv(other[, axis, level, fill_value])	Get Floating division of dataframe and other, element-wise (binary operator *rtruediv*).
sample([n, frac, replace, weights, ...])	Return a random sample of items from an axis of object.
select_dtypes([include, exclude])	Return a subset of the DataFrame's columns based on the column dtypes.
sem([axis, skipna, level, ddof, numeric_only])	Return unbiased standard error of the mean over requested axis.
set_axis(labels[, axis, inplace])	Assign desired index to given axis.
set_flags(*[, copy, allows_duplicate_labels])	Return a new object with updated flags.
set_index(keys[, drop, append, inplace, ...])	Set the DataFrame index using existing columns.
shift([periods, freq, axis, fill_value])	Shift index by desired number of periods with an optional time *freq*.
skew([axis, skipna, level, numeric_only])	Return unbiased skew over requested axis.
slice_shift([periods, axis])	(DEPRECATED) Equivalent to *shift* without copying data.
sort_index([axis, level, ascending, ...])	Sort object by labels (along an axis).
sort_values(by[, axis, ascending, inplace, ...])	Sort by the values along either axis.
sparse	alias of `pandas.core.arrays.sparse.accessor.SparseFrameAccessor`
squeeze([axis])	Squeeze 1 dimensional axis objects into scalars.
stack([level, dropna])	Stack the prescribed level(s) from columns to index.
std([axis, skipna, level, ddof, numeric_only])	Return sample standard deviation over requested axis.
sub(other[, axis, level, fill_value])	Get Subtraction of dataframe and other, element-wise (binary operator *sub*).
subtract(other[, axis, level, fill_value])	Get Subtraction of dataframe and other, element-wise (binary operator *sub*).
sum([axis, skipna, level, numeric_only, ...])	Return the sum of the values over the requested axis.
swapaxes(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately.

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swaplevel([i, j, axis])	Swap levels i and j in a MultiIndex on a particular axis.
tail([n])	Return the last *n* rows.
take(indices[, axis, is_copy])	Return the elements in the given *positional* indices along an axis.
to_clipboard([excel, sep])	Copy object to the system clipboard.
to_csv([path_or_buf, sep, na_rep, ...])	Write object to a comma-separated values (csv) file.
to_dict([orient, into])	Convert the DataFrame to a dictionary.
to_excel(excel_writer[, sheet_name, na_rep, ...])	Write object to an Excel sheet.
to_feather(path, **kwargs)	Write a DataFrame to the binary Feather format.
to_gbq(destination_table[, project_id, ...])	Write a DataFrame to a Google BigQuery table.
to_hdf(path_or_buf, key[, mode, complevel, ...])	Write the contained data to an HDF5 file using HDFStore.
to_html([buf, columns, col_space, header, ...])	Render a DataFrame as an HTML table.
to_json([path_or_buf, orient, date_format, ...])	Convert the object to a JSON string.
to_latex([buf, columns, col_space, header, ...])	Render object to a LaTeX tabular, longtable, or nested table/tabular.
to_markdown([buf, mode, index, storage_options])	Print DataFrame in Markdown-friendly format.
to_numpy([dtype, copy, na_value])	Convert the DataFrame to a NumPy array.
to_parquet([path, engine, compression, ...])	Write a DataFrame to the binary parquet format.
to_period([freq, axis, copy])	Convert DataFrame from DatetimeIndex to PeriodIndex.
to_pickle(path[, compression, protocol, ...])	Pickle (serialize) object to file.
to_records([index, column_dtypes, index_dtypes])	Convert DataFrame to a NumPy record array.
to_sql(name, con[, schema, if_exists, ...])	Write records stored in a DataFrame to a SQL database.
to_stata(path[, convert_dates, write_index, ...])	Export DataFrame object to Stata dta format.
to_string([buf, columns, col_space, header, ...])	Render a DataFrame to a console-friendly tabular output.
to_timestamp([freq, how, axis, copy])	Cast to DatetimeIndex of timestamps, at *beginning* of period.
to_xarray()	Return an xarray object from the pandas object.
transform(func[, axis])	Call `func` on self producing a DataFrame with transformed values.
transpose(*args[, copy])	Transpose index and columns.
truediv(other[, axis, level, fill_value])	Get Floating division of dataframe and other, element-wise (binary operator *truediv*).
truncate([before, after, axis, copy])	Truncate a Series or DataFrame before and after some index value.
tshift([periods, freq, axis])	(DEPRECATED) Shift the time index, using the index's frequency if available.
tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
tz_localize(tz[, axis, level, copy, ...])	Localize tz-naive index of a Series or DataFrame to target time zone.
unstack([level, fill_value])	Pivot a level of the (necessarily hierarchical) index labels.
update(other[, join, overwrite, ...])	Modify in place using non-NA values from another DataFrame.

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value_counts([subset, normalize, sort, ...])	Return a Series containing counts of unique rows in the DataFrame.
var([axis, skipna, level, ddof, numeric_only])	Return unbiased variance over requested axis.
where(cond[, other, inplace, axis, level, ...])	Replace values where the condition is False.
xs(key[, axis, level, drop_level])	Return cross-section from the Series/DataFrame.

pandas.DataFrame.abs

DataFrame.**abs**()

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

Returns

abs Series/DataFrame containing the absolute value of each element.

See also:

numpy.absolute Calculate the absolute value element-wise.

Notes

For `complex` inputs, `1.2 + 1j`, the absolute value is $\sqrt{a^2 + b^2}$.

Examples

Absolute numeric values in a Series.

```
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0    1.10
1    2.00
2    3.33
3    4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.

```
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0    1.56205
dtype: float64
```

Absolute numeric values in a Series with a Timedelta element.

```
>>> s = pd.Series([pd.Timedelta('1 days')])
>>> s.abs()
0   1 days
dtype: timedelta64[ns]
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```
>>> df = pd.DataFrame({
...     'a': [4, 5, 6, 7],
...     'b': [10, 20, 30, 40],
...     'c': [100, 50, -30, -50]
... })
>>> df
     a    b    c
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50
>>> df.loc[(df.c - 43).abs().argsort()]
     a    b    c
1    5   20   50
0    4   10  100
2    6   30  -30
3    7   40  -50
```

pandas.DataFrame.add

DataFrame.**add**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Addition of dataframe and other, element-wise (binary operator *add*).

Equivalent to `dataframe + other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *radd*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
```

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```
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.add_prefix

DataFrame.**add_prefix**(*prefix*)

Prefix labels with string *prefix*.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

Parameters

prefix [str] The string to add before each label.

Returns

Series or DataFrame New Series or DataFrame with updated labels.

See also:

Series.add_suffix Suffix row labels with string *suffix*.

DataFrame.add_suffix Suffix column labels with string *suffix*.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_prefix('item_')
item_0    1
item_1    2
item_2    3
item_3    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```
>>> df.add_prefix('col_')
     col_A  col_B
0       1       3
1       2       4
```

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```
2       3       5
3       4       6
```

pandas.DataFrame.add_suffix

DataFrame.**add_suffix**(*suffix*)

Suffix labels with string *suffix*.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

Parameters

suffix [str] The string to add after each label.

Returns

Series or DataFrame New Series or DataFrame with updated labels.

See also:

Series.add_prefix Prefix row labels with string *prefix*.

DataFrame.add_prefix Prefix column labels with string *prefix*.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_suffix('_item')
0_item    1
1_item    2
2_item    3
3_item    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```
>>> df.add_suffix('_col')
     A_col  B_col
0       1       3
1       2       4
2       3       5
3       4       6
```

pandas.DataFrame.agg

DataFrame.**agg**(*func=None*, *axis=0*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

axis [{0 or 'index', 1 or 'columns'}, default 0] If 0 or 'index': apply function to each column. If 1 or 'columns': apply function to each row.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from *numpy* aggregation functions (*mean*, *median*, *prod*, *sum*, *std*, *var*), where the default is to compute the aggregation of the flattened array, e.g., `numpy.mean(arr_2d)` as opposed to `numpy.mean(arr_2d, axis=0)`.

***agg* is an alias for *aggregate*. Use the alias.**

See also:

DataFrame.apply Perform any type of operations.

DataFrame.transform Perform transformation type operations.

core.groupby.GroupBy Perform operations over groups.

core.resample.Resampler Perform operations over resampled bins.

core.window.Rolling Perform operations over rolling window.

core.window.Expanding Perform operations over expanding window.

core.window.ExponentialMovingWindow Perform operation over exponential weighted window.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> df = pd.DataFrame([[1, 2, 3],
...                    [4, 5, 6],
...                    [7, 8, 9],
...                    [np.nan, np.nan, np.nan]],
...                   columns=['A', 'B', 'C'])
```

Aggregate these functions over the rows.

```
>>> df.agg(['sum', 'min'])
        A     B     C
sum  12.0  15.0  18.0
min   1.0   2.0   3.0
```

Different aggregations per column.

```
>>> df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
        A    B
sum  12.0  NaN
min   1.0  2.0
max   NaN  8.0
```

Aggregate different functions over the columns and rename the index of the resulting DataFrame.

```
>>> df.agg(x=('A', max), y=('B', 'min'), z=('C', np.mean))
     A    B    C
x  7.0  NaN  NaN
y  NaN  2.0  NaN
z  NaN  NaN  6.0
```

Aggregate over the columns.

```
>>> df.agg("mean", axis="columns")
0    2.0
1    5.0
2    8.0
3    NaN
dtype: float64
```

pandas.DataFrame.aggregate

DataFrame.**aggregate**(*func=None*, *axis=0*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

axis [{0 or 'index', 1 or 'columns'}, default 0] If 0 or 'index': apply function to each column. If 1 or 'columns': apply function to each row.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from *numpy* aggregation functions (*mean*, *median*, *prod*, *sum*, *std*, *var*), where the default is to compute the aggregation of the flattened array, e.g., `numpy.mean(arr_2d)` as opposed to `numpy.mean(arr_2d, axis=0)`.

***agg* is an alias for *aggregate*. Use the alias.**

See also:

DataFrame.apply Perform any type of operations.

DataFrame.transform Perform transformation type operations.

core.groupby.GroupBy Perform operations over groups.

core.resample.Resampler Perform operations over resampled bins.

core.window.Rolling Perform operations over rolling window.

core.window.Expanding Perform operations over expanding window.

core.window.ExponentialMovingWindow Perform operation over exponential weighted window.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> df = pd.DataFrame([[1, 2, 3],
...                    [4, 5, 6],
...                    [7, 8, 9],
...                    [np.nan, np.nan, np.nan]],
...                   columns=['A', 'B', 'C'])
```

Aggregate these functions over the rows.

```
>>> df.agg(['sum', 'min'])
        A     B     C
sum  12.0  15.0  18.0
min   1.0   2.0   3.0
```

Different aggregations per column.

```
>>> df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
        A    B
sum  12.0  NaN
min   1.0  2.0
max   NaN  8.0
```

Aggregate different functions over the columns and rename the index of the resulting DataFrame.

```
>>> df.agg(x=('A', max), y=('B', 'min'), z=('C', np.mean))
     A    B    C
x  7.0  NaN  NaN
y  NaN  2.0  NaN
z  NaN  NaN  6.0
```

Aggregate over the columns.

```
>>> df.agg("mean", axis="columns")
0    2.0
1    5.0
2    8.0
3    NaN
dtype: float64
```

pandas.DataFrame.align

DataFrame.**align**(*other*, *join='outer'*, *axis=None*, *level=None*, *copy=True*, *fill_value=None*, *method=None*, *limit=None*, *fill_axis=0*, *broadcast_axis=None*)

Align two objects on their axes with the specified join method.

Join method is specified for each axis Index.

Parameters

other [DataFrame or Series]

join [{'outer', 'inner', 'left', 'right'}, default 'outer']

axis [allowed axis of the other object, default None] Align on index (0), columns (1), or both (None).

level [int or level name, default None] Broadcast across a level, matching Index values on the passed MultiIndex level.

copy [bool, default True] Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any "compatible" value.

method [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series:

- pad / ffill: propagate last valid observation forward to next valid.
- backfill / bfill: use NEXT valid observation to fill gap.

limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

fill_axis [{0 or 'index', 1 or 'columns'}, default 0] Filling axis, method and limit.

broadcast_axis [{0 or 'index', 1 or 'columns'}, default None] Broadcast values along this axis, if aligning two objects of different dimensions.

Returns

(left, right) [(DataFrame, type of other)] Aligned objects.

pandas.DataFrame.all

DataFrame.**all**(*axis=0*, *bool_only=None*, *skipna=True*, *level=None*, ***kwargs*)

Return whether all elements are True, potentially over an axis.

Returns True unless there at least one element within a series or along a Dataframe axis that is False or equivalent (e.g. zero or empty).

Parameters

axis [{0 or 'index', 1 or 'columns', None}, default 0] Indicate which axis or axes should be reduced.

- 0 / 'index' : reduce the index, return a Series whose index is the original column labels.

- 1 / 'columns' : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be True, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

****kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame If level is specified, then, DataFrame is returned; otherwise, Series is returned.

See also:

Series.all Return True if all elements are True.

DataFrame.any Return True if one (or more) elements are True.

Examples

Series

```
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
>>> pd.Series([]).all()
True
>>> pd.Series([np.nan]).all()
True
>>> pd.Series([np.nan]).all(skipna=False)
True
```

DataFrames

Create a dataframe from a dictionary.

```
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
   col1   col2
0  True   True
1  True  False
```

Default behaviour checks if column-wise values all return True.

```
>>> df.all()
col1     True
col2    False
dtype: bool
```

Specify `axis='columns'` to check if row-wise values all return True.

```
>>> df.all(axis='columns')
0     True
1    False
dtype: bool
```

Or `axis=None` for whether every value is True.

```
>>> df.all(axis=None)
False
```

pandas.DataFrame.any

`DataFrame.`**`any`**(*axis=0*, *bool_only=None*, *skipna=True*, *level=None*, ***kwargs*)

Return whether any element is True, potentially over an axis.

Returns False unless there is at least one element within a series or along a Dataframe axis that is True or equivalent (e.g. non-zero or non-empty).

Parameters

axis [{0 or 'index', 1 or 'columns', None}, default 0] Indicate which axis or axes should be reduced.

- 0 / 'index' : reduce the index, return a Series whose index is the original column labels.
- 1 / 'columns' : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be False, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

****kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame If level is specified, then, DataFrame is returned; otherwise, Series is returned.

See also:

`numpy.any` Numpy version of this method.

`Series.any` Return whether any element is True.

`Series.all` Return whether all elements are True.

`DataFrame.any` Return whether any element is True over requested axis.

`DataFrame.all` Return whether all elements are True over requested axis.

Examples

Series

For Series input, the output is a scalar indicating whether any element is True.

```
>>> pd.Series([False, False]).any()
False
>>> pd.Series([True, False]).any()
True
>>> pd.Series([]).any()
False
>>> pd.Series([np.nan]).any()
False
>>> pd.Series([np.nan]).any(skipna=False)
True
```

DataFrame

Whether each column contains at least one True element (the default).

```
>>> df = pd.DataFrame({"A": [1, 2], "B": [0, 2], "C": [0, 0]})
>>> df
   A  B  C
0  1  0  0
1  2  2  0
```

```
>>> df.any()
A     True
B     True
C    False
dtype: bool
```

Aggregating over the columns.

```
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 2]})
>>> df
       A  B
0   True  1
1  False  2
```

```
>>> df.any(axis='columns')
0    True
1    True
dtype: bool
```

```
>>> df = pd.DataFrame({"A": [True, False], "B": [1, 0]})
>>> df
       A  B
0   True  1
1  False  0
```

```
>>> df.any(axis='columns')
0    True
1    False
dtype: bool
```

Aggregating over the entire DataFrame with `axis=None`.

```
>>> df.any(axis=None)
True
```

any for an empty DataFrame is an empty Series.

```
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```

pandas.DataFrame.append

DataFrame.**append**(*other*, *ignore_index=False*, *verify_integrity=False*, *sort=False*)

Append rows of *other* to the end of caller, returning a new object.

Columns in *other* that are not in the caller are added as new columns.

Parameters

other [DataFrame or Series/dict-like object, or list of these] The data to append.

ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, . . . , n - 1.

verify_integrity [bool, default False] If True, raise ValueError on creating index with duplicates.

sort [bool, default False] Sort columns if the columns of *self* and *other* are not aligned.

Changed in version 1.0.0: Changed to not sort by default.

Returns

DataFrame

See also:

concat General function to concatenate DataFrame or Series objects.

Notes

If a list of dict/series is passed and the keys are all contained in the DataFrame's index, the order of the columns in the resulting DataFrame will be unchanged.

Iteratively appending rows to a DataFrame can be more computationally intensive than a single concatenate. A better solution is to append those rows to a list and then concatenate the list with the original DataFrame all at once.

Examples

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=list('AB'))
>>> df
   A  B
0  1  2
1  3  4
>>> df2 = pd.DataFrame([[5, 6], [7, 8]], columns=list('AB'))
>>> df.append(df2)
   A  B
```

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```
0   1   2
1   3   4
0   5   6
1   7   8
```

With *ignore_index* set to True:

```
>>> df.append(df2, ignore_index=True)
   A  B
0  1  2
1  3  4
2  5  6
3  7  8
```

The following, while not recommended methods for generating DataFrames, show two ways to generate a DataFrame from multiple data sources.

Less efficient:

```
>>> df = pd.DataFrame(columns=['A'])
>>> for i in range(5):
...     df = df.append({'A': i}, ignore_index=True)
>>> df
   A
0  0
1  1
2  2
3  3
4  4
```

More efficient:

```
>>> pd.concat([pd.DataFrame([i], columns=['A']) for i in range(5)],
...           ignore_index=True)
   A
0  0
1  1
2  2
3  3
4  4
```

pandas.DataFrame.apply

`DataFrame.`**`apply`**(*func*, *axis=0*, *raw=False*, *result_type=None*, *args=()*, ***kwds*)

Apply a function along an axis of the DataFrame.

Objects passed to the function are Series objects whose index is either the DataFrame's index (`axis=0`) or the DataFrame's columns (`axis=1`). By default (`result_type=None`), the final return type is inferred from the return type of the applied function. Otherwise, it depends on the *result_type* argument.

Parameters

func [function] Function to apply to each column or row.

axis [{0 or 'index', 1 or 'columns'}, default 0] Axis along which the function is applied:

- 0 or 'index': apply function to each column.
- 1 or 'columns': apply function to each row.

raw [bool, default False] Determines if row or column is passed as a Series or ndarray object:

- `False` : passes each row or column as a Series to the function.
- `True` : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

result_type [{'expand', 'reduce', 'broadcast', None}, default None] These only act when `axis=1` (columns):

- 'expand' : list-like results will be turned into columns.
- 'reduce' : returns a Series if possible rather than expanding list-like results. This is the opposite of 'expand'.
- 'broadcast' : results will be broadcast to the original shape of the DataFrame, the original index and columns will be retained.

The default behaviour (None) depends on the return value of the applied function: list-like results will be returned as a Series of those. However if the apply function returns a Series these are expanded to columns.

args [tuple] Positional arguments to pass to *func* in addition to the array/series.

****kwds** Additional keyword arguments to pass as keywords arguments to *func*.

Returns

Series or DataFrame Result of applying `func` along the given axis of the DataFrame.

See also:

DataFrame.applymap For elementwise operations.

DataFrame.aggregate Only perform aggregating type operations.

DataFrame.transform Only perform transforming type operations.

Examples

```
>>> df = pd.DataFrame([[4, 9]] * 3, columns=['A', 'B'])
>>> df
   A  B
0  4  9
1  4  9
2  4  9
```

Using a numpy universal function (in this case the same as `np.sqrt(df)`):

```
>>> df.apply(np.sqrt)
     A    B
0  2.0  3.0
1  2.0  3.0
2  2.0  3.0
```

Using a reducing function on either axis

```
>>> df.apply(np.sum, axis=0)
A    12
B    27
dtype: int64
```

```
>>> df.apply(np.sum, axis=1)
0    13
1    13
2    13
dtype: int64
```

Returning a list-like will result in a Series

```
>>> df.apply(lambda x: [1, 2], axis=1)
0    [1, 2]
1    [1, 2]
2    [1, 2]
dtype: object
```

Passing `result_type='expand'` will expand list-like results to columns of a Dataframe

```
>>> df.apply(lambda x: [1, 2], axis=1, result_type='expand')
   0  1
0  1  2
1  1  2
2  1  2
```

Returning a Series inside the function is similar to passing `result_type='expand'`. The resulting column names will be the Series index.

```
>>> df.apply(lambda x: pd.Series([1, 2], index=['foo', 'bar']), axis=1)
   foo  bar
0    1    2
1    1    2
2    1    2
```

Passing `result_type='broadcast'` will ensure the same shape result, whether list-like or scalar is returned by the function, and broadcast it along the axis. The resulting column names will be the originals.

```
>>> df.apply(lambda x: [1, 2], axis=1, result_type='broadcast')
   A  B
0  1  2
1  1  2
2  1  2
```

pandas.DataFrame.applymap

DataFrame.**applymap**(*func*, *na_action=None*)

Apply a function to a Dataframe elementwise.

This method applies a function that accepts and returns a scalar to every element of a DataFrame.

Parameters

func [callable] Python function, returns a single value from a single value.

na_action [{None, 'ignore'}, default None] If 'ignore', propagate NaN values, without passing them to func.

New in version 1.2.

Returns

DataFrame Transformed DataFrame.

See also:

DataFrame.apply Apply a function along input axis of DataFrame.

Examples

```
>>> df = pd.DataFrame([[1, 2.12], [3.356, 4.567]])
>>> df
       0      1
0  1.000  2.120
1  3.356  4.567
```

```
>>> df.applymap(lambda x: len(str(x)))
   0  1
0  3  4
1  5  5
```

Like Series.map, NA values can be ignored:

```
>>> df_copy = df.copy()
>>> df_copy.iloc[0, 0] = pd.NA
>>> df_copy.applymap(lambda x: len(str(x)), na_action='ignore')
      0  1
0  <NA>  4
1     5  5
```

Note that a vectorized version of *func* often exists, which will be much faster. You could square each number elementwise.

```
>>> df.applymap(lambda x: x**2)
           0          1
0   1.000000   4.494400
1  11.262736  20.857489
```

But it's better to avoid applymap in that case.

```
>>> df ** 2
           0          1
0   1.000000   4.494400
1  11.262736  20.857489
```

pandas.DataFrame.asfreq

DataFrame.**asfreq**(*freq*, *method=None*, *how=None*, *normalize=False*, *fill_value=None*)

Convert TimeSeries to specified frequency.

Optionally provide filling method to pad/backfill missing values.

Returns the original data conformed to a new index with the specified frequency. `resample` is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

Parameters

freq [DateOffset or str] Frequency DateOffset or string.

method [{'backfill'/'bfill', 'pad'/'ffill'}, default None] Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):

- 'pad' / 'ffill': propagate last valid observation forward to next valid
- 'backfill' / 'bfill': use NEXT valid observation to fill.

how [{'start', 'end'}, default end] For PeriodIndex only (see PeriodIndex.asfreq).

normalize [bool, default False] Whether to reset output index to midnight.

fill_value [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

Returns

Same type as caller Object converted to the specified frequency.

See also:

reindex Conform DataFrame to new index with optional filling logic.

Notes

To learn more about the frequency strings, please see this link.

Examples

Start by creating a series with 4 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
                     s
2000-01-01 00:00:00    0.0
2000-01-01 00:01:00    NaN
2000-01-01 00:02:00    2.0
2000-01-01 00:03:00    3.0
```

Upsample the series into 30 second bins.

```
>>> df.asfreq(freq='30S')
                     s
2000-01-01 00:00:00    0.0
```

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```
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    NaN
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    NaN
2000-01-01 00:03:00    3.0
```

Upsample again, providing a `fill value`.

```
>>> df.asfreq(freq='30S', fill_value=9.0)
                       s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    9.0
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    9.0
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    9.0
2000-01-01 00:03:00    3.0
```

Upsample again, providing a `method`.

```
>>> df.asfreq(freq='30S', method='bfill')
                       s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    2.0
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    3.0
2000-01-01 00:03:00    3.0
```

pandas.DataFrame.asof

DataFrame.**asof**(*where*, *subset=None*)

Return the last row(s) without any NaNs before *where*.

The last row (for each element in *where*, if list) without any NaN is taken. In case of a *DataFrame*, the last row without NaN considering only the subset of columns (if not *None*)

If there is no good value, NaN is returned for a Series or a Series of NaN values for a DataFrame

Parameters

where [date or array-like of dates] Date(s) before which the last row(s) are returned.

subset [str or array-like of str, default *None*] For DataFrame, if not *None*, only use these columns to check for NaNs.

Returns

scalar, Series, or DataFrame The return can be:

- scalar : when *self* is a Series and *where* is a scalar
- Series: when *self* is a Series and *where* is an array-like, or when *self* is a DataFrame and *where* is a scalar
- DataFrame : when *self* is a DataFrame and *where* is an array-like

Return scalar, Series, or DataFrame.

See also:

merge_asof Perform an asof merge. Similar to left join.

Notes

Dates are assumed to be sorted. Raises if this is not the case.

Examples

A Series and a scalar *where*.

```
>>> s = pd.Series([1, 2, np.nan, 4], index=[10, 20, 30, 40])
>>> s
10    1.0
20    2.0
30    NaN
40    4.0
dtype: float64
```

```
>>> s.asof(20)
2.0
```

For a sequence *where*, a Series is returned. The first value is NaN, because the first element of *where* is before the first index value.

```
>>> s.asof([5, 20])
5     NaN
20    2.0
dtype: float64
```

Missing values are not considered. The following is `2.0`, not NaN, even though NaN is at the index location for `30`.

```
>>> s.asof(30)
2.0
```

Take all columns into consideration

```
>>> df = pd.DataFrame({'a': [10, 20, 30, 40, 50],
...                    'b': [None, None, None, None, 500]},
...                   index=pd.DatetimeIndex(['2018-02-27 09:01:00',
...                                           '2018-02-27 09:02:00',
...                                           '2018-02-27 09:03:00',
...                                           '2018-02-27 09:04:00',
...                                           '2018-02-27 09:05:00']))
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                           '2018-02-27 09:04:30']))
                     a   b
2018-02-27 09:03:30 NaN NaN
2018-02-27 09:04:30 NaN NaN
```

Take a single column into consideration

```
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                           '2018-02-27 09:04:30']),
...         subset=['a'])
                         a   b
2018-02-27 09:03:30   30.0 NaN
2018-02-27 09:04:30   40.0 NaN
```

pandas.DataFrame.assign

DataFrame.**assign**(***kwargs*)

Assign new columns to a DataFrame.

Returns a new object with all original columns in addition to new ones. Existing columns that are re-assigned will be overwritten.

Parameters

****kwargs** [dict of {str: callable or Series}] The column names are keywords. If the values are callable, they are computed on the DataFrame and assigned to the new columns. The callable must not change input DataFrame (though pandas doesn't check it). If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

Returns

DataFrame A new DataFrame with the new columns in addition to all the existing columns.

Notes

Assigning multiple columns within the same `assign` is possible. Later items in '**kwargs' may refer to newly created or modified columns in 'df'; items are computed and assigned into 'df' in order.

Examples

```
>>> df = pd.DataFrame({'temp_c': [17.0, 25.0]},
...                   index=['Portland', 'Berkeley'])
>>> df
          temp_c
Portland    17.0
Berkeley    25.0
```

Where the value is a callable, evaluated on *df*:

```
>>> df.assign(temp_f=lambda x: x.temp_c * 9 / 5 + 32)
          temp_c  temp_f
Portland    17.0    62.6
Berkeley    25.0    77.0
```

Alternatively, the same behavior can be achieved by directly referencing an existing Series or sequence:

```
>>> df.assign(temp_f=df['temp_c'] * 9 / 5 + 32)
          temp_c  temp_f
```

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```
Portland    17.0    62.6
Berkeley    25.0    77.0
```

You can create multiple columns within the same assign where one of the columns depends on another one defined within the same assign:

```
>>> df.assign(temp_f=lambda x: x['temp_c'] * 9 / 5 + 32,
...           temp_k=lambda x: (x['temp_f'] +  459.67) * 5 / 9)
          temp_c  temp_f  temp_k
Portland    17.0    62.6  290.15
Berkeley    25.0    77.0  298.15
```

pandas.DataFrame.astype

DataFrame.**astype**(*dtype*, *copy=True*, *errors='raise'*)

Cast a pandas object to a specified dtype `dtype`.

Parameters

dtype [data type, or dict of column name -> data type] Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use {col: dtype, ...}, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame's columns to column-specific types.

copy [bool, default True] Return a copy when `copy=True` (be very careful setting `copy=False` as changes to values then may propagate to other pandas objects).

errors [{'raise', 'ignore'}, default 'raise'] Control raising of exceptions on invalid data for provided dtype.

- `raise` : allow exceptions to be raised
- `ignore` : suppress exceptions. On error return original object.

Returns

casted [same type as caller]

See also:

to_datetime Convert argument to datetime.

to_timedelta Convert argument to timedelta.

to_numeric Convert argument to a numeric type.

numpy.ndarray.astype Cast a numpy array to a specified type.

Examples

Create a DataFrame:

```
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```

Cast all columns to int32:

```
>>> df.astype('int32').dtypes
col1    int32
col2    int32
dtype: object
```

Cast col1 to int32 using a dictionary:

```
>>> df.astype({'col1': 'int32'}).dtypes
col1    int32
col2    int64
dtype: object
```

Create a series:

```
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0    1
1    2
dtype: int32
>>> ser.astype('int64')
0    1
1    2
dtype: int64
```

Convert to categorical type:

```
>>> ser.astype('category')
0    1
1    2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:

```
>>> cat_dtype = pd.api.types.CategoricalDtype(
...     categories=[2, 1], ordered=True)
>>> ser.astype(cat_dtype)
0    1
1    2
dtype: category
Categories (2, int64): [2 < 1]
```

Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```
>>> s1 = pd.Series([1, 2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
>>> s1  # note that s1[0] has changed too
0    10
1     2
dtype: int64
```

Create a series of dates:

```
>>> ser_date = pd.Series(pd.date_range('20200101', periods=3))
>>> ser_date
0   2020-01-01
1   2020-01-02
2   2020-01-03
dtype: datetime64[ns]
```

Datetimes are localized to UTC first before converting to the specified timezone:

```
>>> ser_date.astype('datetime64[ns, US/Eastern]')
0   2019-12-31 19:00:00-05:00
1   2020-01-01 19:00:00-05:00
2   2020-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

pandas.DataFrame.at_time

DataFrame.**at_time**(*time*, *asof=False*, *axis=None*)

Select values at particular time of day (e.g., 9:30AM).

Parameters

time [datetime.time or str]

axis [{0 or 'index', 1 or 'columns'}, default 0] New in version 0.24.0.

Returns

Series or DataFrame

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

between_time Select values between particular times of the day.

first Select initial periods of time series based on a date offset.

last Select final periods of time series based on a date offset.

DatetimeIndex.indexer_at_time Get just the index locations for values at particular time of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
                     A
2018-04-09 00:00:00  1
2018-04-09 12:00:00  2
2018-04-10 00:00:00  3
2018-04-10 12:00:00  4
```

```
>>> ts.at_time('12:00')
                     A
2018-04-09 12:00:00  2
2018-04-10 12:00:00  4
```

pandas.DataFrame.backfill

DataFrame.**backfill**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *DataFrame.fillna()* with `method='bfill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.DataFrame.between_time

DataFrame.**between_time**(*start_time*, *end_time*, *include_start=True*, *include_end=True*, *axis=None*)

Select values between particular times of the day (e.g., 9:00-9:30 AM).

By setting `start_time` to be later than `end_time`, you can get the times that are *not* between the two times.

Parameters

start_time [datetime.time or str] Initial time as a time filter limit.

end_time [datetime.time or str] End time as a time filter limit.

include_start [bool, default True] Whether the start time needs to be included in the result.

include_end [bool, default True] Whether the end time needs to be included in the result.

axis [{0 or 'index', 1 or 'columns'}, default 0] Determine range time on index or columns value.

New in version 0.24.0.

Returns

Series or DataFrame Data from the original object filtered to the specified dates range.

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

at_time Select values at a particular time of the day.

first Select initial periods of time series based on a date offset.

last Select final periods of time series based on a date offset.

DatetimeIndex.indexer_between_time Get just the index locations for values between particular times of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
                     A
2018-04-09 00:00:00  1
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3
2018-04-12 01:00:00  4
```

```
>>> ts.between_time('0:15', '0:45')
                     A
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3
```

You get the times that are *not* between two times by setting `start_time` later than `end_time`:

```
>>> ts.between_time('0:45', '0:15')
                     A
2018-04-09 00:00:00  1
2018-04-12 01:00:00  4
```

pandas.DataFrame.bfill

DataFrame.**bfill**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *DataFrame.fillna()* with `method='bfill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.DataFrame.bool

DataFrame.**bool**()

Return the bool of a single element Series or DataFrame.

This must be a boolean scalar value, either True or False. It will raise a ValueError if the Series or DataFrame does not have exactly 1 element, or that element is not boolean (integer values 0 and 1 will also raise an exception).

Returns

bool The value in the Series or DataFrame.

See also:

Series.astype Change the data type of a Series, including to boolean.

DataFrame.astype Change the data type of a DataFrame, including to boolean.

numpy.bool_ NumPy boolean data type, used by pandas for boolean values.

Examples

The method will only work for single element objects with a boolean value:

```
>>> pd.Series([True]).bool()
True
>>> pd.Series([False]).bool()
False
```

```
>>> pd.DataFrame({'col': [True]}).bool()
True
>>> pd.DataFrame({'col': [False]}).bool()
False
```

pandas.DataFrame.boxplot

DataFrame.**boxplot**(*column=None*, *by=None*, *ax=None*, *fontsize=None*, *rot=0*, *grid=True*, *figsize=None*, *layout=None*, *return_type=None*, *backend=None*, ***kwargs*)

Make a box plot from DataFrame columns.

Make a box-and-whisker plot from DataFrame columns, optionally grouped by some other columns. A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. By default, they extend no more than *1.5 * IQR (IQR = Q3 - Q1)* from the edges of the box, ending at the farthest data point within that interval. Outliers are plotted as separate dots.

For further details see Wikipedia's entry for boxplot.

Parameters

column [str or list of str, optional] Column name or list of names, or vector. Can be any valid input to *pandas.DataFrame.groupby()*.

by [str or array-like, optional] Column in the DataFrame to *pandas.DataFrame.groupby()*. One box-plot will be done per value of columns in *by*.

ax [object of class matplotlib.axes.Axes, optional] The matplotlib axes to be used by boxplot.

fontsize [float or str] Tick label font size in points or as a string (e.g., *large*).

rot [int or float, default 0] The rotation angle of labels (in degrees) with respect to the screen coordinate system.

grid [bool, default True] Setting this to True will show the grid.

figsize [A tuple (width, height) in inches] The size of the figure to create in matplotlib.

layout [tuple (rows, columns), optional] For example, (3, 5) will display the subplots using 3 columns and 5 rows, starting from the top-left.

return_type [{'axes', 'dict', 'both'} or None, default 'axes'] The kind of object to return. The default is `axes`.

- 'axes' returns the matplotlib axes the boxplot is drawn on.
- 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot.
- 'both' returns a namedtuple with the axes and dict.
- when grouping with `by`, a Series mapping columns to `return_type` is returned.

  If `return_type` is *None*, a NumPy array of axes with the same shape as `layout` is returned.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

****kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.boxplot()`.

Returns

result See Notes.

See also:

Series.plot.hist Make a histogram.

matplotlib.pyplot.boxplot Matplotlib equivalent plot.

Notes

The return type depends on the *return_type* parameter:

- 'axes' : object of class matplotlib.axes.Axes
- 'dict' : dict of matplotlib.lines.Line2D objects
- 'both' : a namedtuple with structure (ax, lines)

For data grouped with `by`, return a Series of the above or a numpy array:

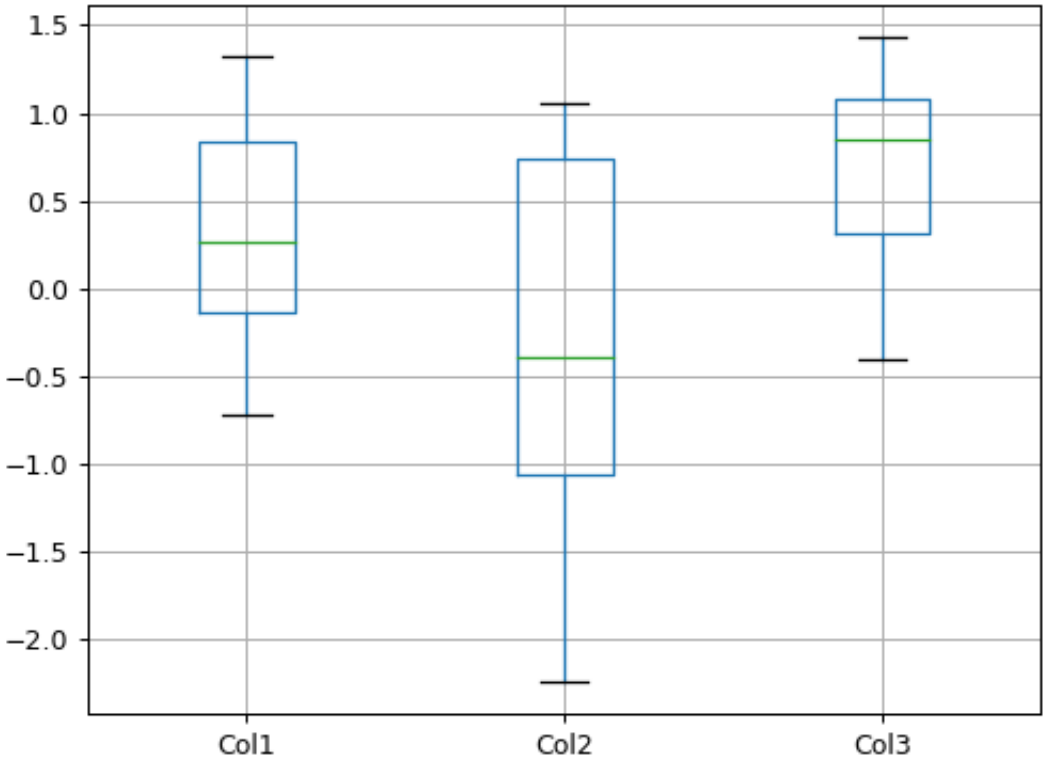
- *Series*
- `array` (for `return_type = None`)

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

Examples

Boxplots can be created for every column in the dataframe by `df.boxplot()` or indicating the columns to be used:

```
>>> np.random.seed(1234)
>>> df = pd.DataFrame(np.random.randn(10, 4),
...                   columns=['Col1', 'Col2', 'Col3', 'Col4'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2', 'Col3'])
```



Boxplots of variables distributions grouped by the values of a third variable can be created using the option `by`. For instance:

```
>>> df = pd.DataFrame(np.random.randn(10, 2),
...                   columns=['Col1', 'Col2'])
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                      'B', 'B', 'B', 'B', 'B'])
>>> boxplot = df.boxplot(by='X')
```

A list of strings (i.e. `['X', 'Y']`) can be passed to boxplot in order to group the data by combination of the variables in the x-axis:

```
>>> df = pd.DataFrame(np.random.randn(10, 3),
...                   columns=['Col1', 'Col2', 'Col3'])
```

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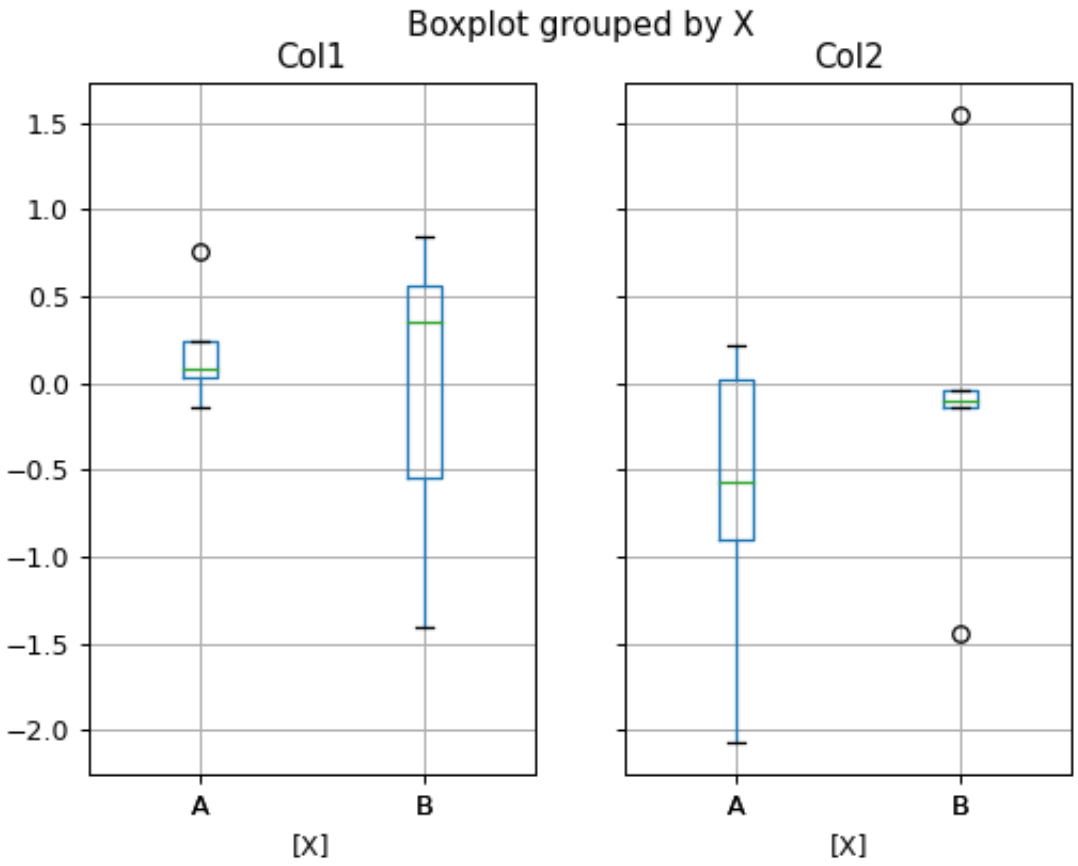
Boxplot grouped by X
Col1
Col2
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
A
B
[X]
A
B
[X]

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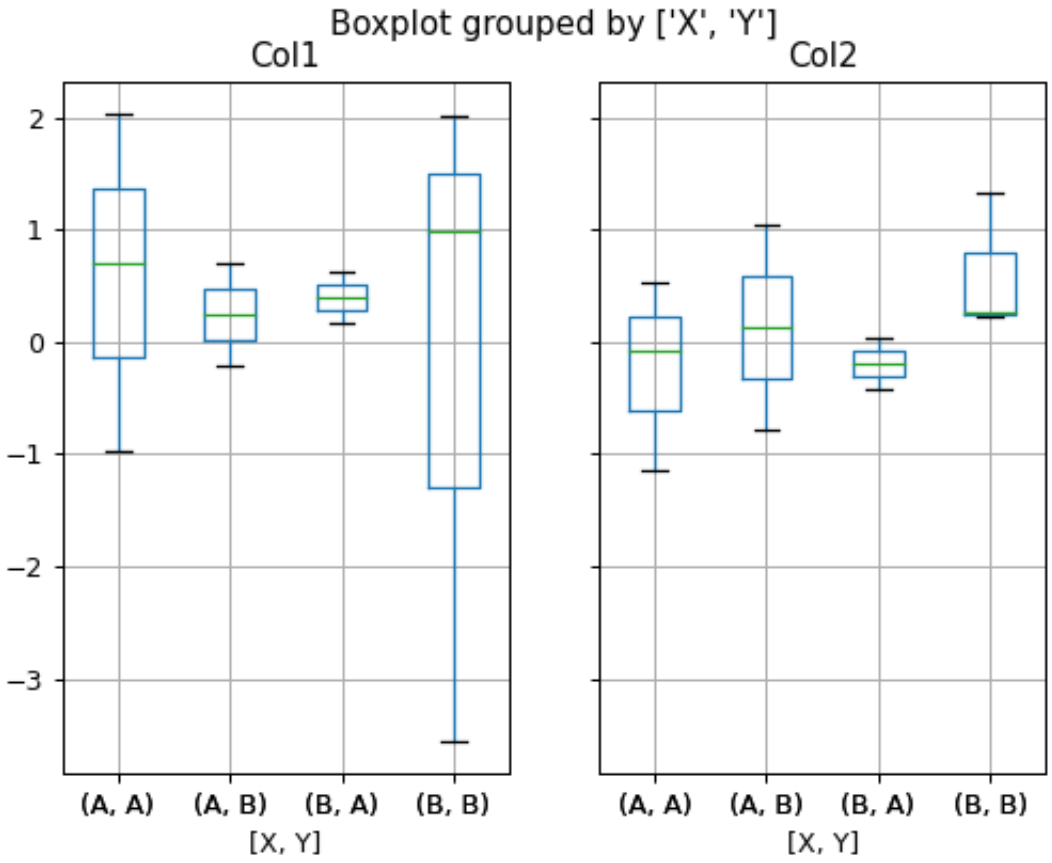
```
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                      'B', 'B', 'B', 'B', 'B'])
>>> df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A',
...                      'B', 'A', 'B', 'A', 'B'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```



The layout of boxplot can be adjusted giving a tuple to `layout`:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      layout=(2, 1))
```

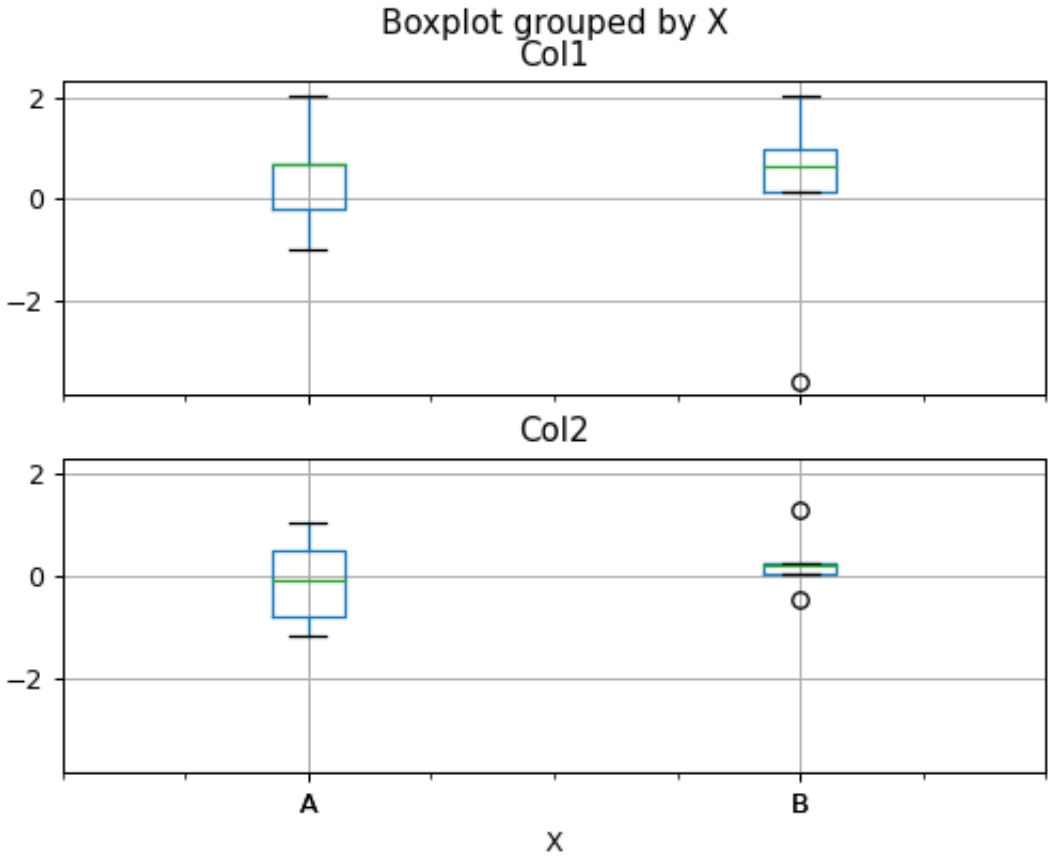
Additional formatting can be done to the boxplot, like suppressing the grid (`grid=False`), rotating the labels in the x-axis (i.e. `rot=45`) or changing the fontsize (i.e. `fontsize=15`):

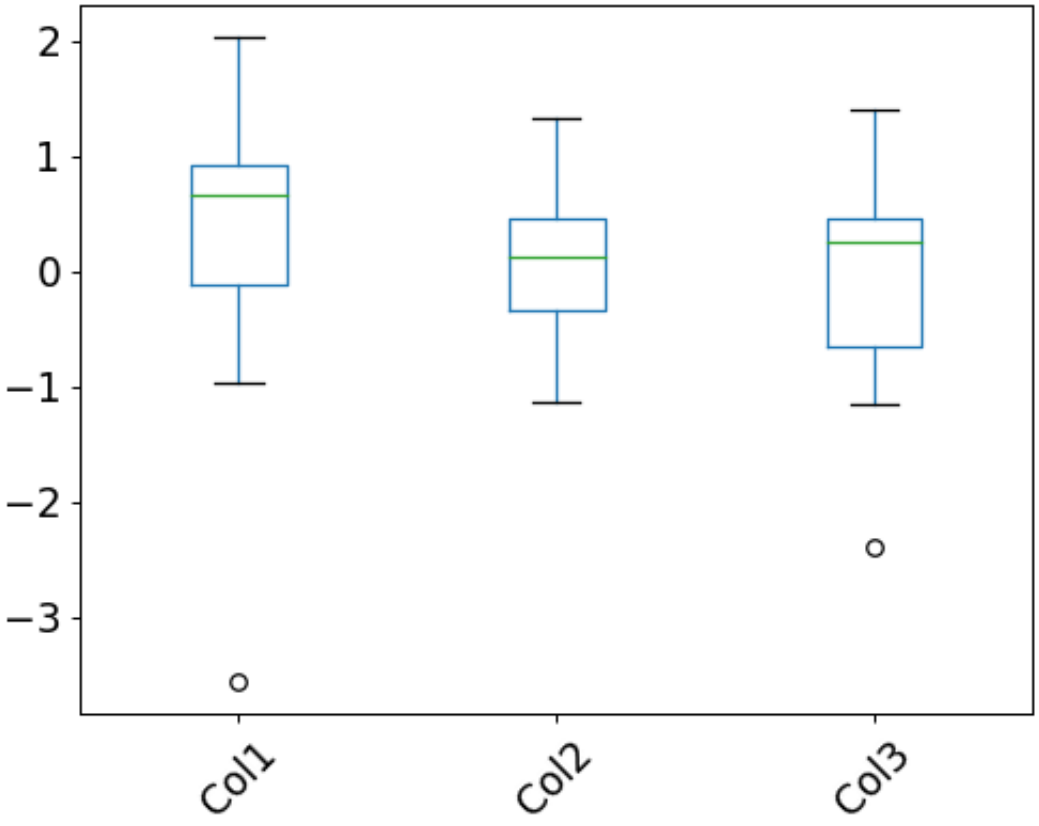
```
>>> boxplot = df.boxplot(grid=False, rot=45, fontsize=15)
```

The parameter `return_type` can be used to select the type of element returned by *boxplot*. When `return_type='axes'` is selected, the matplotlib axes on which the boxplot is drawn are returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], return_type='axes')
>>> type(boxplot)
<class 'matplotlib.axes._subplots.AxesSubplot'>
```

When grouping with `by`, a Series mapping columns to `return_type` is returned:


Boxplot grouped by X
Col1
2
0
−2
Col2
2
0
−2
A
B
X


2
1
0
−1
−2
−3
Col1
Col2
Col3

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      return_type='axes')
>>> type(boxplot)
<class 'pandas.core.series.Series'>
```

If `return_type` is *None*, a NumPy array of axes with the same shape as `layout` is returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      return_type=None)
>>> type(boxplot)
<class 'numpy.ndarray'>
```

pandas.DataFrame.clip

DataFrame.**clip**(*lower=None*, *upper=None*, *axis=None*, *inplace=False*, **args*, ***kwargs*)

Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

Parameters

lower [float or array_like, default None] Minimum threshold value. All values below this threshold will be set to it.

upper [float or array_like, default None] Maximum threshold value. All values above this threshold will be set to it.

axis [int or str axis name, optional] Align object with lower and upper along the given axis.

inplace [bool, default False] Whether to perform the operation in place on the data.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with numpy.

Returns

Series or DataFrame or None Same type as calling object with the values outside the clip boundaries replaced or None if `inplace=True`.

See also:

Series.clip Trim values at input threshold in series.

DataFrame.clip Trim values at input threshold in dataframe.

numpy.clip Clip (limit) the values in an array.

Examples

```
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
   col_0  col_1
0      9     -2
1     -3     -7
2      0      6
3     -1      8
4      5     -5
```

Clips per column using lower and upper thresholds:

```
>>> df.clip(-4, 6)
   col_0  col_1
0      6     -2
1     -3     -4
2      0      6
3     -1      6
4      5     -4
```

Clips using specific lower and upper thresholds per column element:

```
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0    2
1   -4
2   -1
3    6
4    3
dtype: int64
```

```
>>> df.clip(t, t + 4, axis=0)
   col_0  col_1
0      6      2
1     -3     -4
2      0      3
3      6      8
4      5      3
```

pandas.DataFrame.combine

DataFrame.**combine**(*other*, *func*, *fill_value=None*, *overwrite=True*)

Perform column-wise combine with another DataFrame.

Combines a DataFrame with *other* DataFrame using *func* to element-wise combine columns. The row and column indexes of the resulting DataFrame will be the union of the two.

Parameters

other [DataFrame] The DataFrame to merge column-wise.

func [function] Function that takes two series as inputs and return a Series or a scalar. Used to merge the two dataframes column by columns.

fill_value [scalar value, default None] The value to fill NaNs with prior to passing any column to the merge func.

overwrite [bool, default True] If True, columns in *self* that do not exist in *other* will be overwritten with NaNs.

Returns

DataFrame Combination of the provided DataFrames.

See also:

DataFrame.combine_first Combine two DataFrame objects and default to non-null values in frame calling the method.

Examples

Combine using a simple function that chooses the smaller column.

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [4, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> take_smaller = lambda s1, s2: s1 if s1.sum() < s2.sum() else s2
>>> df1.combine(df2, take_smaller)
   A  B
0  0  3
1  0  3
```

Example using a true element-wise combine function.

```
>>> df1 = pd.DataFrame({'A': [5, 0], 'B': [2, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine(df2, np.minimum)
   A  B
0  1  2
1  0  3
```

Using *fill_value* fills Nones prior to passing the column to the merge function.

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [None, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine(df2, take_smaller, fill_value=-5)
   A    B
0  0 -5.0
1  0  4.0
```

However, if the same element in both dataframes is None, that None is preserved

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [None, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [None, 3]})
>>> df1.combine(df2, take_smaller, fill_value=-5)
    A    B
0  0 -5.0
1  0  3.0
```

Example that demonstrates the use of *overwrite* and behavior when the axis differ between the dataframes.

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [4, 4]})
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [-10, 1], }, index=[1, 2])
>>> df1.combine(df2, take_smaller)
     A    B     C
```

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```
0  NaN  NaN   NaN
1  NaN  3.0 -10.0
2  NaN  3.0   1.0
```

```
>>> df1.combine(df2, take_smaller, overwrite=False)
     A    B     C
0  0.0  NaN   NaN
1  0.0  3.0 -10.0
2  NaN  3.0   1.0
```

Demonstrating the preference of the passed in dataframe.

```
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [1, 1], }, index=[1, 2])
>>> df2.combine(df1, take_smaller)
   A    B   C
0  0.0  NaN NaN
1  0.0  3.0 NaN
2  NaN  3.0 NaN
```

```
>>> df2.combine(df1, take_smaller, overwrite=False)
     A    B   C
0  0.0  NaN NaN
1  0.0  3.0 1.0
2  NaN  3.0 1.0
```

pandas.DataFrame.combine_first

DataFrame.**combine_first**(*other*)

Update null elements with value in the same location in *other*.

Combine two DataFrame objects by filling null values in one DataFrame with non-null values from other DataFrame. The row and column indexes of the resulting DataFrame will be the union of the two.

Parameters

other [DataFrame] Provided DataFrame to use to fill null values.

Returns

DataFrame

See also:

DataFrame.combine Perform series-wise operation on two DataFrames using a given function.

Examples

```
>>> df1 = pd.DataFrame({'A': [None, 0], 'B': [None, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine_first(df2)
     A    B
0  1.0  3.0
1  0.0  4.0
```

Null values still persist if the location of that null value does not exist in *other*

```
>>> df1 = pd.DataFrame({'A': [None, 0], 'B': [4, None]})
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [1, 1]}, index=[1, 2])
>>> df1.combine_first(df2)
     A    B    C
0  NaN  4.0  NaN
1  0.0  3.0  1.0
2  NaN  3.0  1.0
```

pandas.DataFrame.compare

DataFrame.**compare**(*other*, *align_axis=1*, *keep_shape=False*, *keep_equal=False*)

Compare to another DataFrame and show the differences.

New in version 1.1.0.

Parameters

other [DataFrame] Object to compare with.

align_axis [{0 or 'index', 1 or 'columns'}, default 1] Determine which axis to align the comparison on.

- **0, or 'index'** [Resulting differences are stacked vertically] with rows drawn alternately from self and other.
- **1, or 'columns'** [Resulting differences are aligned horizontally] with columns drawn alternately from self and other.

keep_shape [bool, default False] If true, all rows and columns are kept. Otherwise, only the ones with different values are kept.

keep_equal [bool, default False] If true, the result keeps values that are equal. Otherwise, equal values are shown as NaNs.

Returns

DataFrame DataFrame that shows the differences stacked side by side.

The resulting index will be a MultiIndex with 'self' and 'other' stacked alternately at the inner level.

Raises

ValueError When the two DataFrames don't have identical labels or shape.

See also:

Series.compare Compare with another Series and show differences.

DataFrame.equals Test whether two objects contain the same elements.

Notes

Matching NaNs will not appear as a difference.

Can only compare identically-labeled (i.e. same shape, identical row and column labels) DataFrames

Examples

```
>>> df = pd.DataFrame(
...     {
...         "col1": ["a", "a", "b", "b", "a"],
...         "col2": [1.0, 2.0, 3.0, np.nan, 5.0],
...         "col3": [1.0, 2.0, 3.0, 4.0, 5.0]
...     },
...     columns=["col1", "col2", "col3"],
... )
>>> df
  col1  col2  col3
0    a   1.0   1.0
1    a   2.0   2.0
2    b   3.0   3.0
3    b   NaN   4.0
4    a   5.0   5.0
```

```
>>> df2 = df.copy()
>>> df2.loc[0, 'col1'] = 'c'
>>> df2.loc[2, 'col3'] = 4.0
>>> df2
  col1  col2  col3
0    c   1.0   1.0
1    a   2.0   2.0
2    b   3.0   4.0
3    b   NaN   4.0
4    a   5.0   5.0
```

Align the differences on columns

```
>>> df.compare(df2)
  col1       col3
  self other self other
0    a     c  NaN   NaN
2  NaN   NaN  3.0   4.0
```

Stack the differences on rows

```
>>> df.compare(df2, align_axis=0)
        col1  col3
0 self     a   NaN
  other    c   NaN
2 self   NaN   3.0
  other  NaN   4.0
```

Keep the equal values

```
>>> df.compare(df2, keep_equal=True)
  col1       col3
```

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```
  self other self other
0    a     c  1.0   1.0
2    b     b  3.0   4.0
```

Keep all original rows and columns

```
>>> df.compare(df2, keep_shape=True)
  col1       col2       col3
  self other self other self other
0    a     c  NaN   NaN  NaN   NaN
1  NaN   NaN  NaN   NaN  NaN   NaN
2  NaN   NaN  NaN   NaN  3.0   4.0
3  NaN   NaN  NaN   NaN  NaN   NaN
4  NaN   NaN  NaN   NaN  NaN   NaN
```

Keep all original rows and columns and also all original values

```
>>> df.compare(df2, keep_shape=True, keep_equal=True)
  col1       col2       col3
  self other self other self other
0    a     c  1.0   1.0  1.0   1.0
1    a     a  2.0   2.0  2.0   2.0
2    b     b  3.0   3.0  3.0   4.0
3    b     b  NaN   NaN  4.0   4.0
4    a     a  5.0   5.0  5.0   5.0
```

pandas.DataFrame.convert_dtypes

DataFrame.**convert_dtypes**(*infer_objects=True*, *convert_string=True*, *convert_integer=True*, *convert_boolean=True*, *convert_floating=True*)

Convert columns to best possible dtypes using dtypes supporting `pd.NA`.

New in version 1.0.0.

Parameters

infer_objects [bool, default True] Whether object dtypes should be converted to the best possible types.

convert_string [bool, default True] Whether object dtypes should be converted to `StringDtype()`.

convert_integer [bool, default True] Whether, if possible, conversion can be done to integer extension types.

convert_boolean [bool, defaults True] Whether object dtypes should be converted to `BooleanDtypes()`.

convert_floating [bool, defaults True] Whether, if possible, conversion can be done to floating extension types. If *convert_integer* is also True, preference will be give to integer dtypes if the floats can be faithfully casted to integers.

New in version 1.2.0.

Returns

Series or DataFrame Copy of input object with new dtype.

See also:

infer_objects Infer dtypes of objects.

to_datetime Convert argument to datetime.

to_timedelta Convert argument to timedelta.

to_numeric Convert argument to a numeric type.

Notes

By default, `convert_dtypes` will attempt to convert a Series (or each Series in a DataFrame) to dtypes that support `pd.NA`. By using the options `convert_string`, `convert_integer`, `convert_boolean` and `convert_boolean`, it is possible to turn off individual conversions to `StringDtype`, the integer extension types, `BooleanDtype` or floating extension types, respectively.

For object-dtyped columns, if `infer_objects` is `True`, use the inference rules as during normal Series/DataFrame construction. Then, if possible, convert to `StringDtype`, `BooleanDtype` or an appropriate integer or floating extension type, otherwise leave as `object`.

If the dtype is integer, convert to an appropriate integer extension type.

If the dtype is numeric, and consists of all integers, convert to an appropriate integer extension type. Otherwise, convert to an appropriate floating extension type.

Changed in version 1.2: Starting with pandas 1.2, this method also converts float columns to the nullable floating extension type.

In the future, as new dtypes are added that support `pd.NA`, the results of this method will change to support those new dtypes.

Examples

```
>>> df = pd.DataFrame(
...     {
...         "a": pd.Series([1, 2, 3], dtype=np.dtype("int32")),
...         "b": pd.Series(["x", "y", "z"], dtype=np.dtype("O")),
...         "c": pd.Series([True, False, np.nan], dtype=np.dtype("O")),
...         "d": pd.Series(["h", "i", np.nan], dtype=np.dtype("O")),
...         "e": pd.Series([10, np.nan, 20], dtype=np.dtype("float")),
...         "f": pd.Series([np.nan, 100.5, 200], dtype=np.dtype("float")),
...     }
... )
```

Start with a DataFrame with default dtypes.

```
>>> df
   a  b      c    d     e      f
0  1  x   True    h  10.0    NaN
1  2  y  False    i   NaN  100.5
2  3  z    NaN  NaN  20.0  200.0
```

```
>>> df.dtypes
a      int32
b     object
c     object
d     object
e    float64
```

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```
f    float64
dtype: object
```

Convert the DataFrame to use best possible dtypes.

```
>>> dfn = df.convert_dtypes()
>>> dfn
   a  b      c     d     e      f
0  1  x   True     h    10   <NA>
1  2  y  False     i  <NA>  100.5
2  3  z   <NA>  <NA>    20  200.0
```

```
>>> dfn.dtypes
a      Int32
b     string
c    boolean
d     string
e      Int64
f    Float64
dtype: object
```

Start with a Series of strings and missing data represented by `np.nan`.

```
>>> s = pd.Series(["a", "b", np.nan])
>>> s
0      a
1      b
2    NaN
dtype: object
```

Obtain a Series with dtype `StringDtype`.

```
>>> s.convert_dtypes()
0       a
1       b
2    <NA>
dtype: string
```

pandas.DataFrame.copy

`DataFrame.`**`copy`**(*deep=True*)

Make a copy of this object's indices and data.

When `deep=True` (default), a new object will be created with a copy of the calling object's data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).

When `deep=False`, a new object will be created without copying the calling object's data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

Parameters

deep [bool, default True] Make a deep copy, including a copy of the data and the indices. With `deep=False` neither the indices nor the data are copied.

Returns

copy [Series or DataFrame] Object type matches caller.

Notes

When `deep=True`, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to *copy.deepcopy* in the Standard Library, which recursively copies object data (see examples below).

While `Index` objects are copied when `deep=True`, the underlying numpy array is not copied for performance reasons. Since `Index` is immutable, the underlying data can be safely shared and a copy is not needed.

Examples

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> s
a    1
b    2
dtype: int64
```

```
>>> s_copy = s.copy()
>>> s_copy
a    1
b    2
dtype: int64
```

Shallow copy versus default (deep) copy:

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> deep = s.copy()
>>> shallow = s.copy(deep=False)
```

Shallow copy shares data and index with original.

```
>>> s is shallow
False
>>> s.values is shallow.values and s.index is shallow.index
True
```

Deep copy has own copy of data and index.

```
>>> s is deep
False
>>> s.values is deep.values or s.index is deep.index
False
```

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

```
>>> s[0] = 3
>>> shallow[1] = 4
>>> s
a    3
b    4
```

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```
dtype: int64
>>> shallow
a    3
b    4
dtype: int64
>>> deep
a    1
b    2
dtype: int64
```

Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

```
>>> s = pd.Series([[1, 2], [3, 4]])
>>> deep = s.copy()
>>> s[0][0] = 10
>>> s
0    [10, 2]
1     [3, 4]
dtype: object
>>> deep
0    [10, 2]
1     [3, 4]
dtype: object
```

pandas.DataFrame.corr

DataFrame.**corr**(*method='pearson'*, *min_periods=1*)

Compute pairwise correlation of columns, excluding NA/null values.

Parameters

method [{'pearson', 'kendall', 'spearman'} or callable] Method of correlation:

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- **callable: callable with input two 1d ndarrays** and returning a float. Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable's behavior.

  New in version 0.24.0.

min_periods [int, optional] Minimum number of observations required per pair of columns to have a valid result. Currently only available for Pearson and Spearman correlation.

Returns

DataFrame Correlation matrix.

See also:

DataFrame.corrwith Compute pairwise correlation with another DataFrame or Series.

Series.corr Compute the correlation between two Series.

Examples

```
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
>>> df = pd.DataFrame([(.2, .3), (.0, .6), (.6, .0), (.2, .1)],
...                   columns=['dogs', 'cats'])
>>> df.corr(method=histogram_intersection)
      dogs  cats
dogs   1.0   0.3
cats   0.3   1.0
```

pandas.DataFrame.corrwith

DataFrame.**corrwith**(*other*, *axis=0*, *drop=False*, *method='pearson'*)

Compute pairwise correlation.

Pairwise correlation is computed between rows or columns of DataFrame with rows or columns of Series or DataFrame. DataFrames are first aligned along both axes before computing the correlations.

Parameters

other [DataFrame, Series] Object with which to compute correlations.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' to compute column-wise, 1 or 'columns' for row-wise.

drop [bool, default False] Drop missing indices from result.

method [{'pearson', 'kendall', 'spearman'} or callable] Method of correlation:

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- **callable: callable with input two 1d ndarrays** and returning a float.

New in version 0.24.0.

Returns

Series Pairwise correlations.

See also:

DataFrame.corr Compute pairwise correlation of columns.

pandas.DataFrame.count

DataFrame.**count**(*axis=0*, *level=None*, *numeric_only=False*)

Count non-NA cells for each column or row.

The values *None*, *NaN*, *NaT*, and optionally *numpy.inf* (depending on *pandas.options.mode.use_inf_as_na*) are considered NA.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] If 0 or 'index' counts are generated for each column. If 1 or 'columns' counts are generated for each row.

level [int or str, optional] If the axis is a *MultiIndex* (hierarchical), count along a particular *level*, collapsing into a *DataFrame*. A *str* specifies the level name.

numeric_only [bool, default False] Include only *float*, *int* or *boolean* data.

Returns

Series or DataFrame For each column/row the number of non-NA/null entries. If *level* is specified returns a *DataFrame*.

See also:

Series.count Number of non-NA elements in a Series.

DataFrame.value_counts Count unique combinations of columns.

DataFrame.shape Number of DataFrame rows and columns (including NA elements).

DataFrame.isna Boolean same-sized DataFrame showing places of NA elements.

Examples

Constructing DataFrame from a dictionary:

```
>>> df = pd.DataFrame({"Person":
...                    ["John", "Myla", "Lewis", "John", "Myla"],
...                    "Age": [24., np.nan, 21., 33, 26],
...                    "Single": [False, True, True, True, False]})
>>> df
   Person   Age  Single
0    John  24.0   False
1    Myla   NaN    True
2   Lewis  21.0    True
3    John  33.0    True
4    Myla  26.0   False
```

Notice the uncounted NA values:

```
>>> df.count()
Person    5
Age       4
Single    5
dtype: int64
```

Counts for each **row**:

```
>>> df.count(axis='columns')
0    3
1    2
2    3
3    3
4    3
dtype: int64
```

Counts for one level of a *MultiIndex*:

```
>>> df.set_index(["Person", "Single"]).count(level="Person")
        Age
Person
John      2
Lewis     1
Myla      1
```

pandas.DataFrame.cov

DataFrame.**cov**(*min_periods=None*, *ddof=1*)

Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the covariance matrix of the columns of the DataFrame.

Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as `NaN`.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

Parameters

min_periods [int, optional] Minimum number of observations required per pair of columns to have a valid result.

ddof [int, default 1] Delta degrees of freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

New in version 1.1.0.

Returns

DataFrame The covariance matrix of the series of the DataFrame.

See also:

Series.cov Compute covariance with another Series.

core.window.ExponentialMovingWindow.cov Exponential weighted sample covariance.

core.window.Expanding.cov Expanding sample covariance.

core.window.Rolling.cov Rolling sample covariance.

Notes

Returns the covariance matrix of the DataFrame's time series. The covariance is normalized by N-ddof.

For DataFrames that have Series that are missing data (assuming that data is missing at random) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

Examples

```
>>> df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],
...                   columns=['dogs', 'cats'])
>>> df.cov()
          dogs      cats
dogs  0.666667 -1.000000
cats -1.000000  1.666667
```

```
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(1000, 5),
...                   columns=['a', 'b', 'c', 'd', 'e'])
>>> df.cov()
          a         b         c         d         e
a  0.998438 -0.020161  0.059277 -0.008943  0.014144
b -0.020161  1.059352 -0.008543 -0.024738  0.009826
c  0.059277 -0.008543  1.010670 -0.001486 -0.000271
d -0.008943 -0.024738 -0.001486  0.921297 -0.013692
e  0.014144  0.009826 -0.000271 -0.013692  0.977795
```

Minimum number of periods

This method also supports an optional `min_periods` keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(20, 3),
...                   columns=['a', 'b', 'c'])
>>> df.loc[df.index[:5], 'a'] = np.nan
>>> df.loc[df.index[5:10], 'b'] = np.nan
>>> df.cov(min_periods=12)
          a         b         c
a  0.316741       NaN -0.150812
b       NaN  1.248003  0.191417
c -0.150812  0.191417  0.895202
```

pandas.DataFrame.cummax

DataFrame.**cummax**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame Return cumulative maximum of Series or DataFrame.

See also:

core.window.Expanding.max Similar functionality but ignores NaN values.

DataFrame.max Return the maximum over DataFrame axis.

DataFrame.cummax Return cumulative maximum over DataFrame axis.

DataFrame.cummin Return cumulative minimum over DataFrame axis.

DataFrame.cumsum Return cumulative sum over DataFrame axis.

DataFrame.cumprod Return cumulative product over DataFrame axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummax()
0    2.0
1    NaN
2    5.0
3    5.0
4    5.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummax(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummax()
     A    B
0  2.0  1.0
1  3.0  NaN
2  3.0  1.0
```

To iterate over columns and find the maximum in each row, use `axis=1`

```
>>> df.cummax(axis=1)
     A    B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

pandas.DataFrame.cummin

DataFrame.**cummin**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame Return cumulative minimum of Series or DataFrame.

See also:

core.window.Expanding.min Similar functionality but ignores `NaN` values.

DataFrame.min Return the minimum over DataFrame axis.

DataFrame.cummax Return cumulative maximum over DataFrame axis.

DataFrame.cummin Return cumulative minimum over DataFrame axis.

DataFrame.cumsum Return cumulative sum over DataFrame axis.

DataFrame.cumprod Return cumulative product over DataFrame axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummin()
0    2.0
1    NaN
2    2.0
3   -1.0
4   -1.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummin(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummin()
     A    B
0  2.0  1.0
1  2.0  NaN
2  1.0  0.0
```

To iterate over columns and find the minimum in each row, use `axis=1`

```
>>> df.cummin(axis=1)
     A    B
```

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```
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

pandas.DataFrame.cumprod

DataFrame.**cumprod**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame Return cumulative product of Series or DataFrame.

See also:

core.window.Expanding.prod Similar functionality but ignores NaN values.

DataFrame.prod Return the product over DataFrame axis.

DataFrame.cummax Return cumulative maximum over DataFrame axis.

DataFrame.cummin Return cumulative minimum over DataFrame axis.

DataFrame.cumsum Return cumulative sum over DataFrame axis.

DataFrame.cumprod Return cumulative product over DataFrame axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumprod()
0     2.0
1     NaN
2    10.0
3   -10.0
4    -0.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumprod(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                   columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumprod()
     A    B
0  2.0  1.0
1  6.0  NaN
2  6.0  0.0
```

To iterate over columns and find the product in each row, use `axis=1`

```
>>> df.cumprod(axis=1)
     A    B
0  2.0  2.0
1  3.0  NaN
2  1.0  0.0
```

pandas.DataFrame.cumsum

DataFrame.**cumsum**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

***args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame Return cumulative sum of Series or DataFrame.

See also:

core.window.Expanding.sum Similar functionality but ignores NaN values.

DataFrame.sum Return the sum over DataFrame axis.

DataFrame.cummax Return cumulative maximum over DataFrame axis.

DataFrame.cummin Return cumulative minimum over DataFrame axis.

DataFrame.cumsum Return cumulative sum over DataFrame axis.

DataFrame.cumprod Return cumulative product over DataFrame axis.

Examples

Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumsum()
0    2.0
1    NaN
2    7.0
3    6.0
4    6.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumsum(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumsum()
     A    B
0  2.0  1.0
1  5.0  NaN
2  6.0  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```
>>> df.cumsum(axis=1)
     A    B
0  2.0  3.0
1  3.0  NaN
2  1.0  1.0
```

pandas.DataFrame.describe

`DataFrame.`**`describe`**(*percentiles=None*, *include=None*, *exclude=None*, *datetime_is_numeric=False*)

Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding `NaN` values.

Analyzes both numeric and object series, as well as `DataFrame` column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

Parameters

percentiles [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is `[.25, .5, .75]`, which returns the 25th, 50th, and 75th percentiles.

include ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for `Series`. Here are the options:

- 'all' : All columns of the input will be included in the output.
- A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use `'category'`
- None (default) : The result will include all numeric columns.

exclude [list-like of dtypes or None (default), optional,] A black list of data types to omit from the result. Ignored for `Series`. Here are the options:

- A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To exclude pandas categorical columns, use `'category'`
- None (default) : The result will exclude nothing.

datetime_is_numeric [bool, default False] Whether to treat datetime dtypes as numeric. This affects statistics calculated for the column. For DataFrame input, this also controls whether datetime columns are included by default.

New in version 1.1.0.

Returns

Series or DataFrame Summary statistics of the Series or Dataframe provided.

See also:

DataFrame.count Count number of non-NA/null observations.

DataFrame.max Maximum of the values in the object.

DataFrame.min Minimum of the values in the object.

DataFrame.mean Mean of the values.

DataFrame.std Standard deviation of the observations.

DataFrame.select_dtypes Subset of a DataFrame including/excluding columns based on their dtype.

Notes

For numeric data, the result's index will include `count`, `mean`, `std`, `min`, `max` as well as lower, `50` and upper percentiles. By default the lower percentile is `25` and the upper percentile is `75`. The `50` percentile is the same as the median.

For object data (e.g. strings or timestamps), the result's index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value's frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns,

the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The *include* and *exclude* parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`.

Examples

Describing a numeric `Series`.

```
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
dtype: float64
```

Describing a categorical `Series`.

```
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count     4
unique    3
top       a
freq      2
dtype: object
```

Describing a timestamp `Series`.

```
>>> s = pd.Series([
...   np.datetime64("2000-01-01"),
...   np.datetime64("2010-01-01"),
...   np.datetime64("2010-01-01")
... ])
>>> s.describe(datetime_is_numeric=True)
count                      3
mean     2006-09-01 08:00:00
min      2000-01-01 00:00:00
25%      2004-12-31 12:00:00
50%      2010-01-01 00:00:00
75%      2010-01-01 00:00:00
max      2010-01-01 00:00:00
dtype: object
```

Describing a `DataFrame`. By default only numeric fields are returned.

```
>>> df = pd.DataFrame({'categorical': pd.Categorical(['d','e','f']),
...                    'numeric': [1, 2, 3],
...                    'object': ['a', 'b', 'c']
...                   })
>>> df.describe()
       numeric
```

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```
count      3.0
mean       2.0
std        1.0
min        1.0
25%        1.5
50%        2.0
75%        2.5
max        3.0
```

Describing all columns of a `DataFrame` regardless of data type.

```
>>> df.describe(include='all')
       categorical  numeric object
count            3      3.0      3
unique           3      NaN      3
top              f      NaN      a
freq             1      NaN      1
mean           NaN      2.0    NaN
std            NaN      1.0    NaN
min            NaN      1.0    NaN
25%            NaN      1.5    NaN
50%            NaN      2.0    NaN
75%            NaN      2.5    NaN
max            NaN      3.0    NaN
```

Describing a column from a `DataFrame` by accessing it as an attribute.

```
>>> df.numeric.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a `DataFrame` description.

```
>>> df.describe(include=[np.number])
       numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%        1.5
50%        2.0
75%        2.5
max        3.0
```

Including only string columns in a `DataFrame` description.

```
>>> df.describe(include=[object])
       object
count       3
```

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```
unique      3
top         a
freq        1
```

Including only categorical columns from a `DataFrame` description.

```
>>> df.describe(include=['category'])
       categorical
count            3
unique           3
top              d
freq             1
```

Excluding numeric columns from a `DataFrame` description.

```
>>> df.describe(exclude=[np.number])
       categorical object
count            3      3
unique           3      3
top              f      a
freq             1      1
```

Excluding object columns from a `DataFrame` description.

```
>>> df.describe(exclude=[object])
       categorical  numeric
count            3      3.0
unique           3      NaN
top              f      NaN
freq             1      NaN
mean           NaN      2.0
std            NaN      1.0
min            NaN      1.0
25%            NaN      1.5
50%            NaN      2.0
75%            NaN      2.5
max            NaN      3.0
```

pandas.DataFrame.diff

`DataFrame.`**`diff`**(*periods=1*, *axis=0*)

First discrete difference of element.

Calculates the difference of a Dataframe element compared with another element in the Dataframe (default is element in previous row).

Parameters

periods [int, default 1] Periods to shift for calculating difference, accepts negative values.

axis [{0 or 'index', 1 or 'columns'}, default 0] Take difference over rows (0) or columns (1).

Returns

Dataframe First differences of the Series.

See also:

`Dataframe.pct_change` Percent change over given number of periods.

`Dataframe.shift` Shift index by desired number of periods with an optional time freq.

`Series.diff` First discrete difference of object.

Notes

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`. The result is calculated according to current dtype in Dataframe, however dtype of the result is always float64.

Examples

Difference with previous row

```
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
...                    'b': [1, 1, 2, 3, 5, 8],
...                    'c': [1, 4, 9, 16, 25, 36]})
>>> df
   a  b   c
0  1  1   1
1  2  1   4
2  3  2   9
3  4  3  16
4  5  5  25
5  6  8  36
```

```
>>> df.diff()
     a    b     c
0  NaN  NaN   NaN
1  1.0  0.0   3.0
2  1.0  1.0   5.0
3  1.0  1.0   7.0
4  1.0  2.0   9.0
5  1.0  3.0  11.0
```

Difference with previous column

```
>>> df.diff(axis=1)
    a  b   c
0 NaN  0   0
1 NaN -1   3
2 NaN -1   7
3 NaN -1  13
4 NaN  0  20
5 NaN  2  28
```

Difference with 3rd previous row

```
>>> df.diff(periods=3)
     a    b     c
0  NaN  NaN   NaN
1  NaN  NaN   NaN
2  NaN  NaN   NaN
```

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```
3  3.0  2.0  15.0
4  3.0  4.0  21.0
5  3.0  6.0  27.0
```

Difference with following row

```
>>> df.diff(periods=-1)
     a    b     c
0 -1.0  0.0  -3.0
1 -1.0 -1.0  -5.0
2 -1.0 -1.0  -7.0
3 -1.0 -2.0  -9.0
4 -1.0 -3.0 -11.0
5  NaN  NaN   NaN
```

Overflow in input dtype

```
>>> df = pd.DataFrame({'a': [1, 0]}, dtype=np.uint8)
>>> df.diff()
       a
0    NaN
1  255.0
```

pandas.DataFrame.div

DataFrame.**div**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rtruediv*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.divide

DataFrame.**divide**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rtruediv*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.dot

DataFrame.**dot**(*other*)

Compute the matrix multiplication between the DataFrame and other.

This method computes the matrix product between the DataFrame and the values of an other Series, DataFrame or a numpy array.

It can also be called using `self @ other` in Python >= 3.5.

Parameters

other [Series, DataFrame or array-like] The other object to compute the matrix product with.

Returns

Series or DataFrame If other is a Series, return the matrix product between self and other as a Series. If other is a DataFrame or a numpy.array, return the matrix product of self and other in a DataFrame of a np.array.

See also:

Series.dot Similar method for Series.

Notes

The dimensions of DataFrame and other must be compatible in order to compute the matrix multiplication. In addition, the column names of DataFrame and the index of other must contain the same values, as they will be aligned prior to the multiplication.

The dot method for Series computes the inner product, instead of the matrix product here.

Examples

Here we multiply a DataFrame with a Series.

```
>>> df = pd.DataFrame([[0, 1, -2, -1], [1, 1, 1, 1]])
>>> s = pd.Series([1, 1, 2, 1])
>>> df.dot(s)
0    -4
1     5
dtype: int64
```

Here we multiply a DataFrame with another DataFrame.

```
>>> other = pd.DataFrame([[0, 1], [1, 2], [-1, -1], [2, 0]])
>>> df.dot(other)
    0   1
0   1   4
1   2   2
```

Note that the dot method give the same result as @

```
>>> df @ other
    0   1
0   1   4
1   2   2
```

The dot method works also if other is an np.array.

```
>>> arr = np.array([[0, 1], [1, 2], [-1, -1], [2, 0]])
>>> df.dot(arr)
    0   1
0   1   4
1   2   2
```

Note how shuffling of the objects does not change the result.

```
>>> s2 = s.reindex([1, 0, 2, 3])
>>> df.dot(s2)
0    -4
1     5
dtype: int64
```

pandas.DataFrame.drop

DataFrame.**drop**(*labels=None*, *axis=0*, *index=None*, *columns=None*, *level=None*, *inplace=False*, *errors='raise'*)

Drop specified labels from rows or columns.

Remove rows or columns by specifying label names and corresponding axis, or by specifying directly index or column names. When using a multi-index, labels on different levels can be removed by specifying the level.

Parameters

labels [single label or list-like] Index or column labels to drop.

axis [{0 or 'index', 1 or 'columns'}, default 0] Whether to drop labels from the index (0 or 'index') or columns (1 or 'columns').

index [single label or list-like] Alternative to specifying axis (`labels, axis=0` is equivalent to `index=labels`).

columns [single label or list-like] Alternative to specifying axis (`labels, axis=1` is equivalent to `columns=labels`).

level [int or level name, optional] For MultiIndex, level from which the labels will be removed.

inplace [bool, default False] If False, return a copy. Otherwise, do operation inplace and return None.

errors [{'ignore', 'raise'}, default 'raise'] If 'ignore', suppress error and only existing labels are dropped.

Returns

DataFrame or None DataFrame without the removed index or column labels or None if `inplace=True`.

Raises

KeyError If any of the labels is not found in the selected axis.

See also:

`DataFrame.loc` Label-location based indexer for selection by label.

DataFrame.dropna Return DataFrame with labels on given axis omitted where (all or any) data are missing.

DataFrame.drop_duplicates Return DataFrame with duplicate rows removed, optionally only considering certain columns.

Series.drop Return Series with specified index labels removed.

Examples

```
>>> df = pd.DataFrame(np.arange(12).reshape(3, 4),
...                   columns=['A', 'B', 'C', 'D'])
>>> df
   A  B   C   D
0  0  1   2   3
1  4  5   6   7
2  8  9  10  11
```

Drop columns

```
>>> df.drop(['B', 'C'], axis=1)
   A   D
0  0   3
1  4   7
2  8  11
```

```
>>> df.drop(columns=['B', 'C'])
   A   D
0  0   3
1  4   7
2  8  11
```

Drop a row by index

```
>>> df.drop([0, 1])
   A  B   C   D
2  8  9  10  11
```

Drop columns and/or rows of MultiIndex DataFrame

```
>>> midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
...                              ['speed', 'weight', 'length']],
...                      codes=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
...                             [0, 1, 2, 0, 1, 2, 0, 1, 2]])
>>> df = pd.DataFrame(index=midx, columns=['big', 'small'],
...                   data=[[45, 30], [200, 100], [1.5, 1], [30, 20],
...                         [250, 150], [1.5, 0.8], [320, 250],
...                         [1, 0.8], [0.3, 0.2]])
>>> df
                big     small
lama    speed   45.0    30.0
        weight  200.0   100.0
        length  1.5     1.0
cow     speed   30.0    20.0
        weight  250.0   150.0
        length  1.5     0.8
falcon  speed   320.0   250.0
```

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```
        weight  1.0     0.8
        length  0.3     0.2
```

```
>>> df.drop(index='cow', columns='small')
                big
lama    speed   45.0
        weight  200.0
        length  1.5
falcon  speed   320.0
        weight  1.0
        length  0.3
```

```
>>> df.drop(index='length', level=1)
                big     small
lama    speed   45.0    30.0
        weight  200.0   100.0
cow     speed   30.0    20.0
        weight  250.0   150.0
falcon  speed   320.0   250.0
        weight  1.0     0.8
```

pandas.DataFrame.drop_duplicates

DataFrame.**drop_duplicates**(*subset=None*, *keep='first'*, *inplace=False*, *ignore_index=False*)

Return DataFrame with duplicate rows removed.

Considering certain columns is optional. Indexes, including time indexes are ignored.

Parameters

subset [column label or sequence of labels, optional] Only consider certain columns for identifying duplicates, by default use all of the columns.

keep [{'first', 'last', False}, default 'first'] Determines which duplicates (if any) to keep. - `first` : Drop duplicates except for the first occurrence. - `last` : Drop duplicates except for the last occurrence. - False : Drop all duplicates.

inplace [bool, default False] Whether to drop duplicates in place or to return a copy.

ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, . . . , n - 1.

New in version 1.0.0.

Returns

DataFrame or None DataFrame with duplicates removed or None if `inplace=True`.

See also:

DataFrame.value_counts Count unique combinations of columns.

Examples

Consider dataset containing ramen rating.

```
>>> df = pd.DataFrame({
...     'brand': ['Yum Yum', 'Yum Yum', 'Indomie', 'Indomie', 'Indomie'],
...     'style': ['cup', 'cup', 'cup', 'pack', 'pack'],
...     'rating': [4, 4, 3.5, 15, 5]
... })
>>> df
    brand style  rating
0  Yum Yum   cup     4.0
1  Yum Yum   cup     4.0
2  Indomie   cup     3.5
3  Indomie  pack    15.0
4  Indomie  pack     5.0
```

By default, it removes duplicate rows based on all columns.

```
>>> df.drop_duplicates()
    brand style  rating
0  Yum Yum   cup     4.0
2  Indomie   cup     3.5
3  Indomie  pack    15.0
4  Indomie  pack     5.0
```

To remove duplicates on specific column(s), use `subset`.

```
>>> df.drop_duplicates(subset=['brand'])
    brand style  rating
0  Yum Yum   cup     4.0
2  Indomie   cup     3.5
```

To remove duplicates and keep last occurrences, use `keep`.

```
>>> df.drop_duplicates(subset=['brand', 'style'], keep='last')
    brand style  rating
1  Yum Yum   cup     4.0
2  Indomie   cup     3.5
4  Indomie  pack     5.0
```

pandas.DataFrame.droplevel

`DataFrame.`**`droplevel`**(*level*, *axis=0*)

Return DataFrame with requested index / column level(s) removed.

New in version 0.24.0.

Parameters

level [int, str, or list-like] If a string is given, must be the name of a level If list-like, elements must be names or positional indexes of levels.

axis [{0 or 'index', 1 or 'columns'}, default 0] Axis along which the level(s) is removed:

- 0 or 'index': remove level(s) in column.
- 1 or 'columns': remove level(s) in row.

Returns

DataFrame DataFrame with requested index / column level(s) removed.

Examples

```
>>> df = pd.DataFrame([
...     [1, 2, 3, 4],
...     [5, 6, 7, 8],
...     [9, 10, 11, 12]
... ]).set_index([0, 1]).rename_axis(['a', 'b'])
```

```
>>> df.columns = pd.MultiIndex.from_tuples([
...     ('c', 'e'), ('d', 'f')
... ], names=['level_1', 'level_2'])
```

```
>>> df
level_1   c   d
level_2   e   f
a b
1 2       3   4
5 6       7   8
9 10     11  12
```

```
>>> df.droplevel('a')
level_1   c   d
level_2   e   f
b
2         3   4
6         7   8
10       11  12
```

```
>>> df.droplevel('level_2', axis=1)
level_1   c   d
a b
1 2       3   4
5 6       7   8
9 10     11  12
```

pandas.DataFrame.dropna

DataFrame.**dropna**(*axis=0*, *how='any'*, *thresh=None*, *subset=None*, *inplace=False*)

Remove missing values.

See the *User Guide* for more on which values are considered missing, and how to work with missing data.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] Determine if rows or columns which contain missing values are removed.

- 0, or 'index' : Drop rows which contain missing values.
- 1, or 'columns' : Drop columns which contain missing value.

Changed in version 1.0.0: Pass tuple or list to drop on multiple axes. Only a single axis is allowed.

how [{'any', 'all'}, default 'any'] Determine if row or column is removed from DataFrame, when we have at least one NA or all NA.

- 'any' : If any NA values are present, drop that row or column.
- 'all' : If all values are NA, drop that row or column.

thresh [int, optional] Require that many non-NA values.

subset [array-like, optional] Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include.

inplace [bool, default False] If True, do operation inplace and return None.

Returns

DataFrame or None DataFrame with NA entries dropped from it or None if `inplace=True`.

See also:

DataFrame.isna Indicate missing values.

DataFrame.notna Indicate existing (non-missing) values.

DataFrame.fillna Replace missing values.

Series.dropna Drop missing values.

Index.dropna Drop missing indices.

Examples

```
>>> df = pd.DataFrame({"name": ['Alfred', 'Batman', 'Catwoman'],
...                    "toy": [np.nan, 'Batmobile', 'Bullwhip'],
...                    "born": [pd.NaT, pd.Timestamp("1940-04-25"),
...                             pd.NaT]})
>>> df
       name        toy       born
0    Alfred        NaN        NaT
1    Batman  Batmobile 1940-04-25
2  Catwoman   Bullwhip        NaT
```

Drop the rows where at least one element is missing.

```
>>> df.dropna()
     name        toy       born
1  Batman  Batmobile 1940-04-25
```

Drop the columns where at least one element is missing.

```
>>> df.dropna(axis='columns')
       name
0    Alfred
1    Batman
2  Catwoman
```

Drop the rows where all elements are missing.

```
>>> df.dropna(how='all')
       name        toy       born
0    Alfred        NaN        NaT
1    Batman  Batmobile 1940-04-25
2  Catwoman   Bullwhip        NaT
```

Keep only the rows with at least 2 non-NA values.

```
>>> df.dropna(thresh=2)
       name        toy       born
1    Batman  Batmobile 1940-04-25
2  Catwoman   Bullwhip        NaT
```

Define in which columns to look for missing values.

```
>>> df.dropna(subset=['name', 'toy'])
       name        toy       born
1    Batman  Batmobile 1940-04-25
2  Catwoman   Bullwhip        NaT
```

Keep the DataFrame with valid entries in the same variable.

```
>>> df.dropna(inplace=True)
>>> df
     name        toy       born
1  Batman  Batmobile 1940-04-25
```

pandas.DataFrame.duplicated

DataFrame.**duplicated**(*subset=None*, *keep='first'*)

Return boolean Series denoting duplicate rows.

Considering certain columns is optional.

Parameters

subset [column label or sequence of labels, optional] Only consider certain columns for identifying duplicates, by default use all of the columns.

keep [{'first', 'last', False}, default 'first'] Determines which duplicates (if any) to mark.

- `first` : Mark duplicates as `True` except for the first occurrence.
- `last` : Mark duplicates as `True` except for the last occurrence.
- False : Mark all duplicates as `True`.

Returns

Series Boolean series for each duplicated rows.

See also:

Index.duplicated Equivalent method on index.

Series.duplicated Equivalent method on Series.

Series.drop_duplicates Remove duplicate values from Series.

DataFrame.drop_duplicates Remove duplicate values from DataFrame.

Examples

Consider dataset containing ramen rating.

```
>>> df = pd.DataFrame({
...     'brand': ['Yum Yum', 'Yum Yum', 'Indomie', 'Indomie', 'Indomie'],
...     'style': ['cup', 'cup', 'cup', 'pack', 'pack'],
...     'rating': [4, 4, 3.5, 15, 5]
... })
>>> df
    brand style  rating
0  Yum Yum   cup     4.0
1  Yum Yum   cup     4.0
2  Indomie   cup     3.5
3  Indomie  pack    15.0
4  Indomie  pack     5.0
```

By default, for each set of duplicated values, the first occurrence is set on False and all others on True.

```
>>> df.duplicated()
0    False
1     True
2    False
3    False
4    False
dtype: bool
```

By using 'last', the last occurrence of each set of duplicated values is set on False and all others on True.

```
>>> df.duplicated(keep='last')
0     True
1    False
2    False
3    False
4    False
dtype: bool
```

By setting `keep` on False, all duplicates are True.

```
>>> df.duplicated(keep=False)
0     True
1     True
2    False
3    False
4    False
dtype: bool
```

To find duplicates on specific column(s), use `subset`.

```
>>> df.duplicated(subset=['brand'])
0    False
1     True
2    False
3     True
4     True
dtype: bool
```

pandas.DataFrame.eq

DataFrame.**eq**(*other*, *axis='columns'*, *level=None*)

Get Equal to of dataframe and other, element-wise (binary operator *eq*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to ==, *!*=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.

DataFrame.ne Compare DataFrames for inequality elementwise.

DataFrame.le Compare DataFrames for less than inequality or equality elementwise.

DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.

DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.

DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. *NaN* values are considered different (i.e. *NaN* != *NaN*).

Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost  revenue
A   250      100
B   150      250
C   100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
    cost  revenue
A  False     True
```

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```
B  False    False
C   True    False
```

```
>>> df.eq(100)
    cost  revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
    cost  revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
    cost  revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
   revenue
A      300
B      250
C      100
D      150
```

```
>>> df.gt(other)
    cost  revenue
```

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```
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                              'revenue': [100, 250, 300, 200, 175, 225]},
...                             index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                    ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost  revenue
Q1 A   250      100
   B   150      250
   C   100      300
Q2 A   150      200
   B   300      175
   C   220      225
```

```
>>> df.le(df_multindex, level=1)
       cost  revenue
Q1 A   True     True
   B   True     True
   C   True     True
Q2 A  False     True
   B   True    False
   C   True    False
```

pandas.DataFrame.equals

DataFrame.**equals**(*other*)

Test whether two objects contain the same elements.

This function allows two Series or DataFrames to be compared against each other to see if they have the same shape and elements. NaNs in the same location are considered equal.

The row/column index do not need to have the same type, as long as the values are considered equal. Corresponding columns must be of the same dtype.

Parameters

other [Series or DataFrame] The other Series or DataFrame to be compared with the first.

Returns

bool True if all elements are the same in both objects, False otherwise.

See also:

Series.eq Compare two Series objects of the same length and return a Series where each element is True if the element in each Series is equal, False otherwise.

DataFrame.eq Compare two DataFrame objects of the same shape and return a DataFrame where each element is True if the respective element in each DataFrame is equal, False otherwise.

testing.assert_series_equal Raises an AssertionError if left and right are not equal. Provides an easy interface to ignore inequality in dtypes, indexes and precision among others.

testing.assert_frame_equal Like assert_series_equal, but targets DataFrames.

numpy.array_equal Return True if two arrays have the same shape and elements, False otherwise.

Examples

```
>>> df = pd.DataFrame({1: [10], 2: [20]})
>>> df
    1   2
0  10  20
```

DataFrames df and exactly_equal have the same types and values for their elements and column labels, which will return True.

```
>>> exactly_equal = pd.DataFrame({1: [10], 2: [20]})
>>> exactly_equal
    1   2
0  10  20
>>> df.equals(exactly_equal)
True
```

DataFrames df and different_column_type have the same element types and values, but have different types for the column labels, which will still return True.

```
>>> different_column_type = pd.DataFrame({1.0: [10], 2.0: [20]})
>>> different_column_type
   1.0  2.0
0   10   20
>>> df.equals(different_column_type)
True
```

DataFrames df and different_data_type have different types for the same values for their elements, and will return False even though their column labels are the same values and types.

```
>>> different_data_type = pd.DataFrame({1: [10.0], 2: [20.0]})
>>> different_data_type
      1     2
0  10.0  20.0
>>> df.equals(different_data_type)
False
```

pandas.DataFrame.eval

DataFrame.**eval**(*expr*, *inplace=False*, ***kwargs*)

Evaluate a string describing operations on DataFrame columns.

Operates on columns only, not specific rows or elements. This allows *eval* to run arbitrary code, which can make you vulnerable to code injection if you pass user input to this function.

Parameters

expr [str] The expression string to evaluate.

inplace [bool, default False] If the expression contains an assignment, whether to perform the operation inplace and mutate the existing DataFrame. Otherwise, a new DataFrame is returned.

****kwargs** See the documentation for *eval()* for complete details on the keyword arguments accepted by *query()*.

Returns

ndarray, scalar, pandas object, or None The result of the evaluation or None if `inplace=True`.

See also:

DataFrame.query Evaluates a boolean expression to query the columns of a frame.

DataFrame.assign Can evaluate an expression or function to create new values for a column.

eval Evaluate a Python expression as a string using various backends.

Notes

For more details see the API documentation for *eval()*. For detailed examples see *enhancing performance with eval*.

Examples

```
>>> df = pd.DataFrame({'A': range(1, 6), 'B': range(10, 0, -2)})
>>> df
   A   B
0  1  10
1  2   8
2  3   6
3  4   4
4  5   2
>>> df.eval('A + B')
0    11
1    10
2     9
3     8
4     7
dtype: int64
```

Assignment is allowed though by default the original DataFrame is not modified.

```
>>> df.eval('C = A + B')
   A   B   C
0  1  10  11
1  2   8  10
2  3   6   9
3  4   4   8
4  5   2   7
>>> df
   A   B
0  1  10
1  2   8
2  3   6
```

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```
3  4   4
4  5   2
```

Use `inplace=True` to modify the original DataFrame.

```
>>> df.eval('C = A + B', inplace=True)
>>> df
   A   B   C
0  1  10  11
1  2   8  10
2  3   6   9
3  4   4   8
4  5   2   7
```

Multiple columns can be assigned to using multi-line expressions:

```
>>> df.eval(
...     '''
... C = A + B
... D = A - B
... '''
... )
   A   B   C  D
0  1  10  11 -9
1  2   8  10 -6
2  3   6   9 -3
3  4   4   8  0
4  5   2   7  3
```

pandas.DataFrame.ewm

DataFrame.**ewm**(*com=None*, *span=None*, *halflife=None*, *alpha=None*, *min_periods=0*, *adjust=True*, *ignore_na=False*, *axis=0*, *times=None*)

Provide exponential weighted (EW) functions.

Available EW functions: `mean()`, `var()`, `std()`, `corr()`, `cov()`.

Exactly one parameter: `com`, `span`, `halflife`, or `alpha` must be provided.

Parameters

com [float, optional] Specify decay in terms of center of mass, $\alpha = 1/(1 + com)$, for $com \geq 0$.

span [float, optional] Specify decay in terms of span, $\alpha = 2/(span+1)$, for $span \geq 1$.

halflife [float, str, timedelta, optional] Specify decay in terms of half-life, $\alpha = 1 - \exp(-\ln(2)/halflife)$, for $halflife > 0$.

If `times` is specified, the time unit (str or timedelta) over which an observation decays to half its value. Only applicable to `mean()` and halflife value will not apply to the other functions.

New in version 1.1.0.

alpha [float, optional] Specify smoothing factor α directly, $0 < \alpha \leq 1$.

min_periods [int, default 0] Minimum number of observations in window required to have a value (otherwise result is NA).

adjust [bool, default True] Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average).

- When `adjust=True` (default), the EW function is calculated using weights $w_i = (1 - \alpha)^i$. For example, the EW moving average of the series $[x_0, x_1, ..., x_t]$ would be:

$$y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2 x_{t-2} + ... + (1 - \alpha)^t x_0}{1 + (1 - \alpha) + (1 - \alpha)^2 + ... + (1 - \alpha)^t}$$

- When `adjust=False`, the exponentially weighted function is calculated recursively:

$$y_0 = x_0$$
$$y_t = (1 - \alpha)y_{t-1} + \alpha x_t,$$

ignore_na [bool, default False] Ignore missing values when calculating weights; specify `True` to reproduce pre-0.15.0 behavior.

- When `ignore_na=False` (default), weights are based on absolute positions. For example, the weights of x_0 and x_2 used in calculating the final weighted average of [x_0, None, x_2] are $(1-\alpha)^2$ and 1 if `adjust=True`, and $(1-\alpha)^2$ and α if `adjust=False`.
- When `ignore_na=True` (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x_0 and x_2 used in calculating the final weighted average of [x_0, None, x_2] are $1 - \alpha$ and 1 if `adjust=True`, and $1 - \alpha$ and α if `adjust=False`.

axis [{0, 1}, default 0] The axis to use. The value 0 identifies the rows, and 1 identifies the columns.

times [str, np.ndarray, Series, default None] New in version 1.1.0.

Times corresponding to the observations. Must be monotonically increasing and `datetime64[ns]` dtype.

If str, the name of the column in the DataFrame representing the times.

If 1-D array like, a sequence with the same shape as the observations.

Only applicable to `mean()`.

Returns

DataFrame A Window sub-classed for the particular operation.

See also:

rolling Provides rolling window calculations.

expanding Provides expanding transformations.

Notes

More details can be found at: *Exponentially weighted windows*.

Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

```
>>> df.ewm(com=0.5).mean()
          B
0  0.000000
1  0.750000
2  1.615385
3  1.615385
4  3.670213
```

Specifying `times` with a timedelta `halflife` when computing mean.

```
>>> times = ['2020-01-01', '2020-01-03', '2020-01-10', '2020-01-15', '2020-
↪01-17']
>>> df.ewm(halflife='4 days', times=pd.DatetimeIndex(times)).mean()
          B
0  0.000000
1  0.585786
2  1.523889
3  1.523889
4  3.233686
```

pandas.DataFrame.expanding

DataFrame.**expanding**(*min_periods=1*, *center=None*, *axis=0*)

Provide expanding transformations.

Parameters

min_periods [int, default 1] Minimum number of observations in window required to have a value (otherwise result is NA).

center [bool, default False] Set the labels at the center of the window.

axis [int or str, default 0]

Returns

a Window sub-classed for the particular operation

See also:

rolling Provides rolling window calculations.

ewm Provides exponential weighted functions.

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

Examples

```
>>> df = pd.DataFrame({"B": [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

```
>>> df.expanding(2).sum()
     B
0  NaN
1  1.0
2  3.0
3  3.0
4  7.0
```

pandas.DataFrame.explode

DataFrame.**explode**(*column*, *ignore_index=False*)

Transform each element of a list-like to a row, replicating index values.

New in version 0.25.0.

Parameters

column [str or tuple] Column to explode.

ignore_index [bool, default False] If True, the resulting index will be labeled 0, 1, . . . , n - 1.

New in version 1.1.0.

Returns

DataFrame Exploded lists to rows of the subset columns; index will be duplicated for these rows.

Raises

ValueError [] if columns of the frame are not unique.

See also:

DataFrame.unstack Pivot a level of the (necessarily hierarchical) index labels.

DataFrame.melt Unpivot a DataFrame from wide format to long format.

Series.explode Explode a DataFrame from list-like columns to long format.

Notes

This routine will explode list-likes including lists, tuples, sets, Series, and np.ndarray. The result dtype of the subset rows will be object. Scalars will be returned unchanged, and empty list-likes will result in a np.nan for that row. In addition, the ordering of rows in the output will be non-deterministic when exploding sets.

Examples

```
>>> df = pd.DataFrame({'A': [[1, 2, 3], 'foo', [], [3, 4]], 'B': 1})
>>> df
           A  B
0  [1, 2, 3]  1
1        foo  1
2         []  1
3     [3, 4]  1
```

```
>>> df.explode('A')
     A  B
0    1  1
0    2  1
0    3  1
1  foo  1
2  NaN  1
3    3  1
3    4  1
```

pandas.DataFrame.ffill

DataFrame.**ffill**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *DataFrame.fillna()* with `method='ffill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.DataFrame.fillna

DataFrame.**fillna**(*value=None*, *method=None*, *axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Fill NA/NaN values using the specified method.

Parameters

value [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

method [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use next valid observation to fill gap.

axis [{0 or 'index', 1 or 'columns'}] Axis along which to fill missing values.

inplace [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

downcast [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

Returns

DataFrame or None Object with missing values filled or None if `inplace=True`.

See also:

interpolate Fill NaN values using interpolation.

reindex Conform object to new index.

asfreq Convert TimeSeries to specified frequency.

Examples

```
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                    [3, 4, np.nan, 1],
...                    [np.nan, np.nan, np.nan, 5],
...                    [np.nan, 3, np.nan, 4]],
...                   columns=list('ABCD'))
>>> df
     A    B   C  D
0  NaN  2.0 NaN  0
1  3.0  4.0 NaN  1
2  NaN  NaN NaN  5
3  NaN  3.0 NaN  4
```

Replace all NaN elements with 0s.

```
>>> df.fillna(0)
    A   B   C   D
0   0.0 2.0 0.0 0
1   3.0 4.0 0.0 1
2   0.0 0.0 0.0 5
3   0.0 3.0 0.0 4
```

We can also propagate non-null values forward or backward.

```
>>> df.fillna(method='ffill')
    A   B   C   D
0   NaN 2.0 NaN 0
1   3.0 4.0 NaN 1
2   3.0 4.0 NaN 5
3   3.0 3.0 NaN 4
```

Replace all NaN elements in column 'A', 'B', 'C', and 'D', with 0, 1, 2, and 3 respectively.

```
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
    A   B   C   D
0   0.0 2.0 2.0 0
1   3.0 4.0 2.0 1
2   0.0 1.0 2.0 5
3   0.0 3.0 2.0 4
```

Only replace the first NaN element.

```
>>> df.fillna(value=values, limit=1)
    A   B   C   D
0   0.0 2.0 2.0 0
1   3.0 4.0 NaN 1
2   NaN 1.0 NaN 5
3   NaN 3.0 NaN 4
```

pandas.DataFrame.filter

DataFrame.**filter**(*items=None*, *like=None*, *regex=None*, *axis=None*)

Subset the dataframe rows or columns according to the specified index labels.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

Parameters

items [list-like] Keep labels from axis which are in items.

like [str] Keep labels from axis for which "like in label == True".

regex [str (regular expression)] Keep labels from axis for which re.search(regex, label) == True.

axis [{0 or 'index', 1 or 'columns', None}, default None] The axis to filter on, expressed either as an index (int) or axis name (str). By default this is the info axis, 'index' for Series, 'columns' for DataFrame.

Returns

same type as input object

See also:

DataFrame.loc Access a group of rows and columns by label(s) or a boolean array.

Notes

The `items`, `like`, and `regex` parameters are enforced to be mutually exclusive.

`axis` defaults to the info axis that is used when indexing with `[]`.

Examples

```
>>> df = pd.DataFrame(np.array(([1, 2, 3], [4, 5, 6])),
...                   index=['mouse', 'rabbit'],
...                   columns=['one', 'two', 'three'])
>>> df
        one  two  three
mouse     1    2      3
rabbit    4    5      6
```

```
>>> # select columns by name
>>> df.filter(items=['one', 'three'])
         one  three
mouse     1      3
rabbit    4      6
```

```
>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
         one  three
mouse     1      3
rabbit    4      6
```

```
>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
         one  two  three
rabbit    4    5      6
```

pandas.DataFrame.first

DataFrame.**first**(*offset*)

Select initial periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the first few rows based on a date offset.

Parameters

offset [str, DateOffset or dateutil.relativedelta] The offset length of the data that will be selected. For instance, '1M' will display all the rows having their index within the first month.

Returns

Series or DataFrame A subset of the caller.

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

last Select final periods of time series based on a date offset.

at_time Select values at a particular time of the day.

between_time Select values between particular times of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
            A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the first 3 days:

```
>>> ts.first('3D')
            A
2018-04-09  1
2018-04-11  2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

pandas.DataFrame.first_valid_index

DataFrame.**first_valid_index**()

Return index for first non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

pandas.DataFrame.floordiv

DataFrame.**floordiv**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Integer division of dataframe and other, element-wise (binary operator *floordiv*).

Equivalent to `dataframe // other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rfloordiv*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.from_dict

classmethod DataFrame.**from_dict**(*data*, *orient='columns'*, *dtype=None*, *columns=None*)

Construct DataFrame from dict of array-like or dicts.

Creates DataFrame object from dictionary by columns or by index allowing dtype specification.

Parameters

data [dict] Of the form {field : array-like} or {field : dict}.

orient [{'columns', 'index'}, default 'columns'] The "orientation" of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass 'columns' (default). Otherwise if the keys should be rows, pass 'index'.

dtype [dtype, default None] Data type to force, otherwise infer.

columns [list, default None] Column labels to use when `orient='index'`. Raises a ValueError if used with `orient='columns'`.

Returns

DataFrame

See also:

DataFrame.from_records DataFrame from structured ndarray, sequence of tuples or dicts, or DataFrame.

DataFrame DataFrame object creation using constructor.

Examples

By default the keys of the dict become the DataFrame columns:

```
>>> data = {'col_1': [3, 2, 1, 0], 'col_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data)
   col_1 col_2
0      3     a
1      2     b
2      1     c
3      0     d
```

Specify `orient='index'` to create the DataFrame using dictionary keys as rows:

```
>>> data = {'row_1': [3, 2, 1, 0], 'row_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data, orient='index')
       0  1  2  3
row_1  3  2  1  0
row_2  a  b  c  d
```

When using the 'index' orientation, the column names can be specified manually:

```
>>> pd.DataFrame.from_dict(data, orient='index',
...                        columns=['A', 'B', 'C', 'D'])
       A  B  C  D
row_1  3  2  1  0
row_2  a  b  c  d
```

pandas.DataFrame.from_records

classmethod DataFrame.**from_records**(*data*, *index=None*, *exclude=None*, *columns=None*, *coerce_float=False*, *nrows=None*)

Convert structured or record ndarray to DataFrame.

Creates a DataFrame object from a structured ndarray, sequence of tuples or dicts, or DataFrame.

Parameters

data [structured ndarray, sequence of tuples or dicts, or DataFrame] Structured input data.

index [str, list of fields, array-like] Field of array to use as the index, alternately a specific set of input labels to use.

exclude [sequence, default None] Columns or fields to exclude.

columns [sequence, default None] Column names to use. If the passed data do not have names associated with them, this argument provides names for the columns. Otherwise this argument indicates the order of the columns in the result (any names not found in the data will become all-NA columns).

coerce_float [bool, default False] Attempt to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets.

nrows [int, default None] Number of rows to read if data is an iterator.

Returns

DataFrame

See also:

DataFrame.from_dict DataFrame from dict of array-like or dicts.

DataFrame DataFrame object creation using constructor.

Examples

Data can be provided as a structured ndarray:

```
>>> data = np.array([(3, 'a'), (2, 'b'), (1, 'c'), (0, 'd')],
...                 dtype=[('col_1', 'i4'), ('col_2', 'U1')])
>>> pd.DataFrame.from_records(data)
   col_1 col_2
0      3     a
1      2     b
2      1     c
3      0     d
```

Data can be provided as a list of dicts:

```
>>> data = [{'col_1': 3, 'col_2': 'a'},
...         {'col_1': 2, 'col_2': 'b'},
...         {'col_1': 1, 'col_2': 'c'},
...         {'col_1': 0, 'col_2': 'd'}]
>>> pd.DataFrame.from_records(data)
   col_1 col_2
0      3     a
1      2     b
2      1     c
3      0     d
```

Data can be provided as a list of tuples with corresponding columns:

```
>>> data = [(3, 'a'), (2, 'b'), (1, 'c'), (0, 'd')]
>>> pd.DataFrame.from_records(data, columns=['col_1', 'col_2'])
   col_1 col_2
0      3     a
1      2     b
2      1     c
3      0     d
```

pandas.DataFrame.ge

DataFrame.**ge**(*other*, *axis='columns'*, *level=None*)

Get Greater than or equal to of dataframe and other, element-wise (binary operator *ge*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to ==, *!*=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.

DataFrame.ne Compare DataFrames for inequality elementwise.

DataFrame.le Compare DataFrames for less than inequality or equality elementwise.

DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.

DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.

DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. *NaN* values are considered different (i.e. *NaN* != *NaN*).

Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost  revenue
A   250      100
B   150      250
C   100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
    cost  revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
    cost  revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
    cost  revenue
A   True     True
```

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```
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
    cost  revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
   revenue
A      300
B      250
C      100
D      150
```

```
>>> df.gt(other)
    cost  revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                              'revenue': [100, 250, 300, 200, 175, 225]},
...                             index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                    ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost  revenue
Q1 A   250      100
```

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```
   B   150      250
   C   100      300
Q2 A   150      200
   B   300      175
   C   220      225
```

```
>>> df.le(df_multindex, level=1)
       cost  revenue
Q1 A   True     True
   B   True     True
   C   True     True
Q2 A  False     True
   B   True    False
   C   True    False
```

pandas.DataFrame.get

DataFrame.**get**(*key*, *default=None*)

Get item from object for given key (ex: DataFrame column).

Returns default value if not found.

Parameters

key [object]

Returns

value [same type as items contained in object]

pandas.DataFrame.groupby

DataFrame.**groupby**(*by=None*, *axis=0*, *level=None*, *as_index=True*, *sort=True*, *group_keys=True*, *squeeze=<object object>*, *observed=False*, *dropna=True*)

Group DataFrame using a mapper or by a Series of columns.

A groupby operation involves some combination of splitting the object, applying a function, and combining the results. This can be used to group large amounts of data and compute operations on these groups.

Parameters

by [mapping, function, label, or list of labels] Used to determine the groups for the groupby. If `by` is a function, it's called on each value of the object's index. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups (the Series' values are first aligned; see `.align()` method). If an ndarray is passed, the values are used as-is to determine the groups. A label or list of labels may be passed to group by the columns in `self`. Notice that a tuple is interpreted as a (single) key.

axis [{0 or 'index', 1 or 'columns'}, default 0] Split along rows (0) or columns (1).

level [int, level name, or sequence of such, default None] If the axis is a MultiIndex (hierarchical), group by a particular level or levels.

as_index [bool, default True] For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively "SQL-style" grouped output.

sort [bool, default True] Sort group keys. Get better performance by turning this off. Note this does not influence the order of observations within each group. Groupby preserves the order of rows within each group.

group_keys [bool, default True] When calling apply, add group keys to index to identify pieces.

squeeze [bool, default False] Reduce the dimensionality of the return type if possible, otherwise return a consistent type.

Deprecated since version 1.1.0.

observed [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

dropna [bool, default True] If True, and if group keys contain NA values, NA values together with row/column will be dropped. If False, NA values will also be treated as the key in groups

New in version 1.1.0.

Returns

DataFrameGroupBy Returns a groupby object that contains information about the groups.

See also:

resample Convenience method for frequency conversion and resampling of time series.

Notes

See the user guide for more.

Examples

```
>>> df = pd.DataFrame({'Animal': ['Falcon', 'Falcon',
...                               'Parrot', 'Parrot'],
...                    'Max Speed': [380., 370., 24., 26.]})
>>> df
   Animal  Max Speed
0  Falcon      380.0
1  Falcon      370.0
2  Parrot       24.0
3  Parrot       26.0
>>> df.groupby(['Animal']).mean()
        Max Speed
Animal
Falcon      375.0
Parrot       25.0
```

Hierarchical Indexes

We can groupby different levels of a hierarchical index using the *level* parameter:

```
>>> arrays = [['Falcon', 'Falcon', 'Parrot', 'Parrot'],
...           ['Captive', 'Wild', 'Captive', 'Wild']]
>>> index = pd.MultiIndex.from_arrays(arrays, names=('Animal', 'Type'))
>>> df = pd.DataFrame({'Max Speed': [390., 350., 30., 20.]},
...                   index=index)
>>> df
                Max Speed
Animal Type
Falcon Captive      390.0
       Wild         350.0
Parrot Captive       30.0
       Wild          20.0
>>> df.groupby(level=0).mean()
        Max Speed
Animal
Falcon      370.0
Parrot       25.0
>>> df.groupby(level="Type").mean()
         Max Speed
Type
Captive      210.0
Wild         185.0
```

We can also choose to include NA in group keys or not by setting *dropna* parameter, the default setting is *True*:

```
>>> l = [[1, 2, 3], [1, None, 4], [2, 1, 3], [1, 2, 2]]
>>> df = pd.DataFrame(l, columns=["a", "b", "c"])
```

```
>>> df.groupby(by=["b"]).sum()
    a   c
b
1.0 2   3
2.0 2   5
```

```
>>> df.groupby(by=["b"], dropna=False).sum()
    a   c
b
1.0 2   3
2.0 2   5
NaN 1   4
```

```
>>> l = [["a", 12, 12], [None, 12.3, 33.], ["b", 12.3, 123], ["a", 1, 1]]
>>> df = pd.DataFrame(l, columns=["a", "b", "c"])
```

```
>>> df.groupby(by="a").sum()
    b     c
a
a   13.0   13.0
b   12.3  123.0
```

```
>>> df.groupby(by="a", dropna=False).sum()
    b     c
a
a   13.0   13.0
```

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```
b   12.3  123.0
NaN 12.3   33.0
```

pandas.DataFrame.gt

DataFrame.**gt**(*other*, *axis='columns'*, *level=None*)

Get Greater than of dataframe and other, element-wise (binary operator *gt*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to ==, *!*=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.

DataFrame.ne Compare DataFrames for inequality elementwise.

DataFrame.le Compare DataFrames for less than inequality or equality elementwise.

DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.

DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.

DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. *NaN* values are considered different (i.e. *NaN* != *NaN*).

Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost  revenue
A   250      100
B   150      250
C   100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
    cost  revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
    cost  revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
    cost  revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
    cost  revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
   revenue
A      300
B      250
C      100
D      150
```

```
>>> df.gt(other)
    cost  revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                              'revenue': [100, 250, 300, 200, 175, 225]},
...                             index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                    ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost  revenue
Q1 A   250      100
   B   150      250
   C   100      300
Q2 A   150      200
   B   300      175
   C   220      225
```

```
>>> df.le(df_multindex, level=1)
       cost  revenue
Q1 A   True     True
   B   True     True
   C   True     True
Q2 A  False     True
   B   True    False
   C   True    False
```

pandas.DataFrame.head

DataFrame.**head**(*n=5*)

Return the first *n* rows.

This function returns the first *n* rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

For negative values of *n*, this function returns all rows except the last *n* rows, equivalent to `df[:-n]`.

Parameters

n [int, default 5] Number of rows to select.

Returns

same type as caller The first *n* rows of the caller object.

See also:

DataFrame.tail Returns the last *n* rows.

Examples

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                               'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
5     parrot
6      shark
7      whale
8      zebra
```

Viewing the first 5 lines

```
>>> df.head()
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
```

Viewing the first *n* lines (three in this case)

```
>>> df.head(3)
      animal
0  alligator
1        bee
2     falcon
```

For negative values of *n*

```
>>> df.head(-3)
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
5     parrot
```

pandas.DataFrame.hist

DataFrame.**hist**(*column=None*, *by=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *ax=None*, *sharex=False*, *sharey=False*, *figsize=None*, *layout=None*, *bins=10*, *backend=None*, *legend=False*, ***kwargs*)

Make a histogram of the DataFrame's.

A histogram is a representation of the distribution of data. This function calls `matplotlib.pyplot.hist()`, on each series in the DataFrame, resulting in one histogram per column.

Parameters

data [DataFrame] The pandas object holding the data.

column [str or sequence] If passed, will be used to limit data to a subset of columns.

by [object, optional] If passed, then used to form histograms for separate groups.

grid [bool, default True] Whether to show axis grid lines.

xlabelsize [int, default None] If specified changes the x-axis label size.

xrot [float, default None] Rotation of x axis labels. For example, a value of 90 displays the x labels rotated 90 degrees clockwise.

ylabelsize [int, default None] If specified changes the y-axis label size.

yrot [float, default None] Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.

ax [Matplotlib axes object, default None] The axes to plot the histogram on.

sharex [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in. Note that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure.

sharey [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.

figsize [tuple] The size in inches of the figure to create. Uses the value in *matplotlib.rcParams* by default.

layout [tuple, optional] Tuple of (rows, columns) for the layout of the histograms.

bins [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

legend [bool, default False] Whether to show the legend.

New in version 1.1.0.

****kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.hist()`.

Returns

matplotlib.AxesSubplot or numpy.ndarray of them

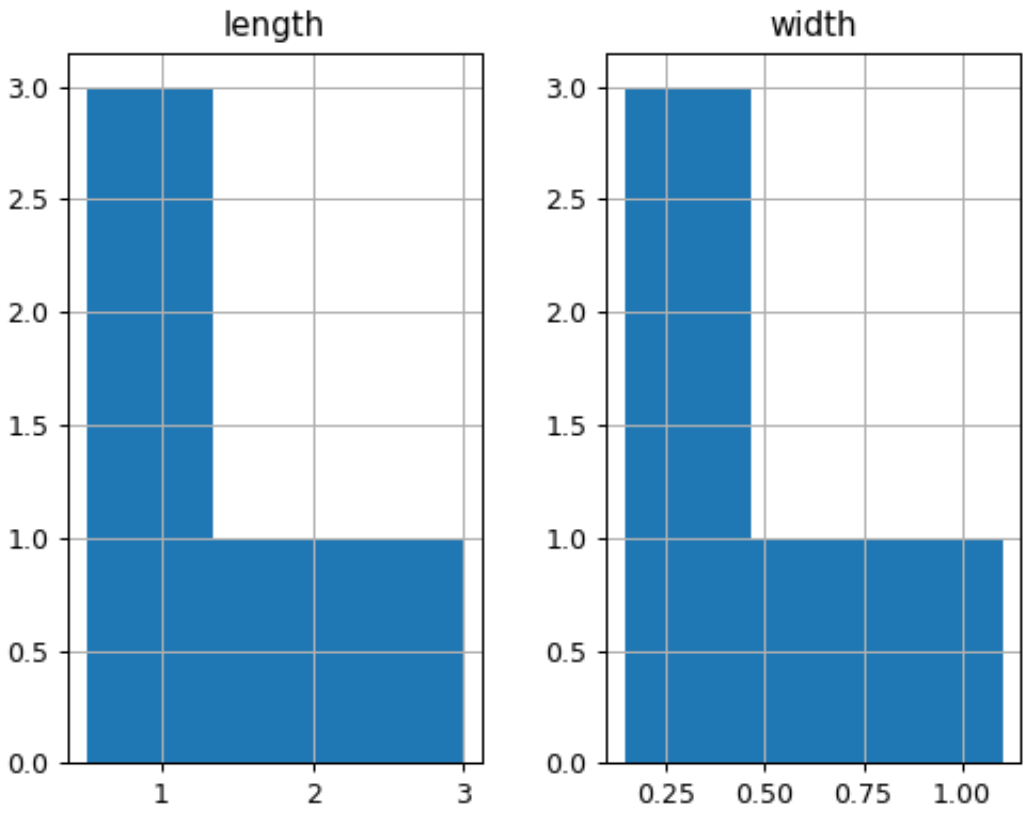
See also:

`matplotlib.pyplot.hist` Plot a histogram using matplotlib.

Examples

This example draws a histogram based on the length and width of some animals, displayed in three bins

```
>>> df = pd.DataFrame({
...     'length': [1.5, 0.5, 1.2, 0.9, 3],
...     'width': [0.7, 0.2, 0.15, 0.2, 1.1]
...     }, index=['pig', 'rabbit', 'duck', 'chicken', 'horse'])
>>> hist = df.hist(bins=3)
```



pandas.DataFrame.idxmax

DataFrame.**idxmax**(*axis=0*, *skipna=True*)

Return index of first occurrence of maximum over requested axis.

NA/null values are excluded.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns

Series Indexes of maxima along the specified axis.

Raises

ValueError

- If the row/column is empty

See also:

Series.idxmax Return index of the maximum element.

Notes

This method is the DataFrame version of `ndarray.argmax`.

Examples

Consider a dataset containing food consumption in Argentina.

```
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
...                    'co2_emissions': [37.2, 19.66, 1712]},
...                    index=['Pork', 'Wheat Products', 'Beef'])
```

```
>>> df
                consumption  co2_emissions
Pork                  10.51         37.20
Wheat Products       103.11         19.66
Beef                  55.48       1712.00
```

By default, it returns the index for the maximum value in each column.

```
>>> df.idxmax()
consumption     Wheat Products
co2_emissions             Beef
dtype: object
```

To return the index for the maximum value in each row, use `axis="columns"`.

```
>>> df.idxmax(axis="columns")
Pork              co2_emissions
Wheat Products     consumption
Beef              co2_emissions
dtype: object
```

pandas.DataFrame.idxmin

DataFrame.**idxmin**(*axis=0*, *skipna=True*)

Return index of first occurrence of minimum over requested axis.

NA/null values are excluded.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns

Series Indexes of minima along the specified axis.

Raises

ValueError

- If the row/column is empty

See also:

Series.idxmin Return index of the minimum element.

Notes

This method is the DataFrame version of `ndarray.argmin`.

Examples

Consider a dataset containing food consumption in Argentina.

```
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
...                    'co2_emissions': [37.2, 19.66, 1712]},
...                    index=['Pork', 'Wheat Products', 'Beef'])
```

```
>>> df
                consumption  co2_emissions
Pork                  10.51         37.20
Wheat Products       103.11         19.66
Beef                  55.48       1712.00
```

By default, it returns the index for the minimum value in each column.

```
>>> df.idxmin()
consumption                Pork
co2_emissions    Wheat Products
dtype: object
```

To return the index for the minimum value in each row, use `axis="columns"`.

```
>>> df.idxmin(axis="columns")
Pork                consumption
Wheat Products    co2_emissions
Beef                consumption
dtype: object
```

pandas.DataFrame.infer_objects

DataFrame.**infer_objects**()

Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

Returns

converted [same type as input object]

See also:

to_datetime Convert argument to datetime.

to_timedelta Convert argument to timedelta.

to_numeric Convert argument to numeric type.

convert_dtypes Convert argument to best possible dtype.

Examples

```
>>> df = pd.DataFrame({"A": ["a", 1, 2, 3]})
>>> df = df.iloc[1:]
>>> df
   A
1  1
2  2
3  3
```

```
>>> df.dtypes
A    object
dtype: object
```

```
>>> df.infer_objects().dtypes
A    int64
dtype: object
```

pandas.DataFrame.info

DataFrame.**info**(*verbose=None*, *buf=None*, *max_cols=None*, *memory_usage=None*, *show_counts=None*, *null_counts=None*)

Print a concise summary of a DataFrame.

This method prints information about a DataFrame including the index dtype and columns, non-null values and memory usage.

Parameters

data [DataFrame] DataFrame to print information about.

verbose [bool, optional] Whether to print the full summary. By default, the setting in `pandas.options.display.max_info_columns` is followed.

buf [writable buffer, defaults to sys.stdout] Where to send the output. By default, the output is printed to sys.stdout. Pass a writable buffer if you need to further process the output.

max_cols [int, optional] When to switch from the verbose to the truncated output. If the DataFrame has more than *max_cols* columns, the truncated output is used. By default, the setting in `pandas.options.display.max_info_columns` is used.

memory_usage [bool, str, optional] Specifies whether total memory usage of the DataFrame elements (including the index) should be displayed. By default, this follows the `pandas.options.display.memory_usage` setting.

True always show memory usage. False never shows memory usage. A value of 'deep' is equivalent to "True with deep introspection". Memory usage is shown in human-readable units (base-2 representation). Without deep introspection a memory estimation is made based in column dtype and number of rows assuming values consume the same memory amount for corresponding dtypes. With deep memory introspection, a real memory usage calculation is performed at the cost of computational resources.

show_counts [bool, optional] Whether to show the non-null counts. By default, this is shown only if the DataFrame is smaller than `pandas.options.display.max_info_rows` and `pandas.options.display.max_info_columns`. A value of True always shows the counts, and False never shows the counts.

null_counts [bool, optional] Deprecated since version 1.2.0: Use show_counts instead.

Returns

None This method prints a summary of a DataFrame and returns None.

See also:

DataFrame.describe Generate descriptive statistics of DataFrame columns.

DataFrame.memory_usage Memory usage of DataFrame columns.

Examples

```
>>> int_values = [1, 2, 3, 4, 5]
>>> text_values = ['alpha', 'beta', 'gamma', 'delta', 'epsilon']
>>> float_values = [0.0, 0.25, 0.5, 0.75, 1.0]
>>> df = pd.DataFrame({"int_col": int_values, "text_col": text_values,
...                    "float_col": float_values})
>>> df
    int_col text_col  float_col
0         1    alpha       0.00
1         2     beta       0.25
2         3    gamma       0.50
3         4    delta       0.75
4         5  epsilon       1.00
```

Prints information of all columns:

```
>>> df.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   int_col    5 non-null      int64
 1   text_col   5 non-null      object
 2   float_col  5 non-null      float64
dtypes: float64(1), int64(1), object(1)
memory usage: 248.0+ bytes
```

Prints a summary of columns count and its dtypes but not per column information:

```
>>> df.info(verbose=False)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Columns: 3 entries, int_col to float_col
dtypes: float64(1), int64(1), object(1)
memory usage: 248.0+ bytes
```

Pipe output of DataFrame.info to buffer instead of sys.stdout, get buffer content and writes to a text file:

```
>>> import io
>>> buffer = io.StringIO()
>>> df.info(buf=buffer)
>>> s = buffer.getvalue()
>>> with open("df_info.txt", "w",
...           encoding="utf-8") as f:
...     f.write(s)
260
```

The *memory_usage* parameter allows deep introspection mode, specially useful for big DataFrames and fine-tune memory optimization:

```
>>> random_strings_array = np.random.choice(['a', 'b', 'c'], 10 ** 6)
>>> df = pd.DataFrame({
...     'column_1': np.random.choice(['a', 'b', 'c'], 10 ** 6),
...     'column_2': np.random.choice(['a', 'b', 'c'], 10 ** 6),
...     'column_3': np.random.choice(['a', 'b', 'c'], 10 ** 6)
```

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```
... })
>>> df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
 #   Column    Non-Null Count    Dtype
---  ------    --------------    -----
 0   column_1  1000000 non-null  object
 1   column_2  1000000 non-null  object
 2   column_3  1000000 non-null  object
dtypes: object(3)
memory usage: 22.9+ MB
```

```
>>> df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
 #   Column    Non-Null Count    Dtype
---  ------    --------------    -----
 0   column_1  1000000 non-null  object
 1   column_2  1000000 non-null  object
 2   column_3  1000000 non-null  object
dtypes: object(3)
memory usage: 165.9 MB
```

pandas.DataFrame.insert

DataFrame.**insert**(*loc*, *column*, *value*, *allow_duplicates=False*)

Insert column into DataFrame at specified location.

Raises a ValueError if *column* is already contained in the DataFrame, unless *allow_duplicates* is set to True.

Parameters

loc [int] Insertion index. Must verify 0 <= loc <= len(columns).

column [str, number, or hashable object] Label of the inserted column.

value [int, Series, or array-like]

allow_duplicates [bool, optional]

pandas.DataFrame.interpolate

DataFrame.**interpolate**(*method='linear'*, *axis=0*, *limit=None*, *inplace=False*, *limit_direction=None*, *limit_area=None*, *downcast=None*, ***kwargs*)

Fill NaN values using an interpolation method.

Please note that only `method='linear'` is supported for DataFrame/Series with a MultiIndex.

Parameters

method [str, default 'linear'] Interpolation technique to use. One of:

- 'linear': Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.

- 'time': Works on daily and higher resolution data to interpolate given length of interval.
- 'index', 'values': use the actual numerical values of the index.
- 'pad': Fill in NaNs using existing values.
- 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'spline', 'barycentric', 'polynomial': Passed to *scipy.interpolate.interp1d*. These methods use the numerical values of the index. Both 'polynomial' and 'spline' require that you also specify an *order* (int), e.g. `df.interpolate(method='polynomial', order=5)`.
- 'krogh', 'piecewise_polynomial', 'spline', 'pchip', 'akima', 'cubicspline': Wrappers around the SciPy interpolation methods of similar names. See *Notes*.
- 'from_derivatives': Refers to *scipy.interpolate.BPoly.from_derivatives* which replaces 'piecewise_polynomial' interpolation method in scipy 0.18.

axis [{{0 or 'index', 1 or 'columns', None}}, default None] Axis to interpolate along.

limit [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

inplace [bool, default False] Update the data in place if possible.

limit_direction [{{'forward', 'backward', 'both'}}, Optional] Consecutive NaNs will be filled in this direction.

If limit is specified:

- If 'method' is 'pad' or 'ffill', 'limit_direction' must be 'forward'.
- If 'method' is 'backfill' or 'bfill', 'limit_direction' must be 'backwards'.

If 'limit' is not specified:

- If 'method' is 'backfill' or 'bfill', the default is 'backward'
- else the default is 'forward'

Changed in version 1.1.0: raises ValueError if *limit_direction* is 'forward' or 'both' and method is 'backfill' or 'bfill'. raises ValueError if *limit_direction* is 'backward' or 'both' and method is 'pad' or 'ffill'.

limit_area [{{*None*, 'inside', 'outside'}}, default None] If limit is specified, consecutive NaNs will be filled with this restriction.

- `None`: No fill restriction.
- 'inside': Only fill NaNs surrounded by valid values (interpolate).
- 'outside': Only fill NaNs outside valid values (extrapolate).

downcast [optional, 'infer' or None, defaults to None] Downcast dtypes if possible.

``**kwargs`` [optional] Keyword arguments to pass on to the interpolating function.

Returns

Series or DataFrame or None Returns the same object type as the caller, interpolated at some or all `NaN` values or None if `inplace=True`.

See also:

fillna Fill missing values using different methods.

scipy.interpolate.Akima1DInterpolator Piecewise cubic polynomials (Akima interpolator).

scipy.interpolate.BPoly.from_derivatives Piecewise polynomial in the Bernstein basis.

scipy.interpolate.interp1d Interpolate a 1-D function.

scipy.interpolate.KroghInterpolator Interpolate polynomial (Krogh interpolator).

scipy.interpolate.PchipInterpolator PCHIP 1-d monotonic cubic interpolation.

scipy.interpolate.CubicSpline Cubic spline data interpolator.

Notes

The 'krogh', 'piecewise_polynomial', 'spline', 'pchip' and 'akima' methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the SciPy documentation and SciPy tutorial.

Examples

Filling in `NaN` in a *`Series`* via linear interpolation.

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0    0.0
1    1.0
2    NaN
3    3.0
dtype: float64
>>> s.interpolate()
0    0.0
1    1.0
2    2.0
3    3.0
dtype: float64
```

Filling in `NaN` in a Series by padding, but filling at most two consecutive `NaN` at a time.

```
>>> s = pd.Series([np.nan, "single_one", np.nan,
...                "fill_two_more", np.nan, np.nan, np.nan,
...                4.71, np.nan])
>>> s
0              NaN
1       single_one
2              NaN
3    fill_two_more
4              NaN
5              NaN
6              NaN
7             4.71
8              NaN
dtype: object
>>> s.interpolate(method='pad', limit=2)
0              NaN
1       single_one
```

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```
2       single_one
3    fill_two_more
4    fill_two_more
5    fill_two_more
6              NaN
7             4.71
8             4.71
dtype: object
```

Filling in `NaN` in a Series via polynomial interpolation or splines: Both 'polynomial' and 'spline' methods require that you also specify an `order` (int).

```
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0    0.000000
1    2.000000
2    4.666667
3    8.000000
dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column 'a' is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column 'b' remains `NaN`, because there is no entry before it to use for interpolation.

```
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                    (np.nan, 2.0, np.nan, np.nan),
...                    (2.0, 3.0, np.nan, 9.0),
...                    (np.nan, 4.0, -4.0, 16.0)],
...                   columns=list('abcd'))
>>> df
     a    b    c     d
0  0.0  NaN -1.0   1.0
1  NaN  2.0  NaN   NaN
2  2.0  3.0  NaN   9.0
3  NaN  4.0 -4.0  16.0
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
     a    b    c     d
0  0.0  NaN -1.0   1.0
1  1.0  2.0 -2.0   5.0
2  2.0  3.0 -3.0   9.0
3  2.0  4.0 -4.0  16.0
```

Using polynomial interpolation.

```
>>> df['d'].interpolate(method='polynomial', order=2)
0     1.0
1     4.0
2     9.0
3    16.0
Name: d, dtype: float64
```

pandas.DataFrame.isin

DataFrame.**isin**(*values*)

Whether each element in the DataFrame is contained in values.

Parameters

values [iterable, Series, DataFrame or dict] The result will only be true at a location if all the labels match. If *values* is a Series, that's the index. If *values* is a dict, the keys must be the column names, which must match. If *values* is a DataFrame, then both the index and column labels must match.

Returns

DataFrame DataFrame of booleans showing whether each element in the DataFrame is contained in values.

See also:

DataFrame.eq Equality test for DataFrame.

Series.isin Equivalent method on Series.

Series.str.contains Test if pattern or regex is contained within a string of a Series or Index.

Examples

```
>>> df = pd.DataFrame({'num_legs': [2, 4], 'num_wings': [2, 0]},
...                   index=['falcon', 'dog'])
>>> df
        num_legs  num_wings
falcon         2          2
dog            4          0
```

When `values` is a list check whether every value in the DataFrame is present in the list (which animals have 0 or 2 legs or wings)

```
>>> df.isin([0, 2])
        num_legs  num_wings
falcon      True       True
dog        False       True
```

When `values` is a dict, we can pass values to check for each column separately:

```
>>> df.isin({'num_wings': [0, 3]})
        num_legs  num_wings
falcon     False      False
dog        False       True
```

When `values` is a Series or DataFrame the index and column must match. Note that 'falcon' does not match based on the number of legs in df2.

```
>>> other = pd.DataFrame({'num_legs': [8, 2], 'num_wings': [0, 2]},
...                      index=['spider', 'falcon'])
>>> df.isin(other)
        num_legs  num_wings
falcon      True       True
dog        False      False
```

pandas.DataFrame.isna

DataFrame.**isna**()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or `numpy.NaN`, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

Returns

DataFrame Mask of bool values for each element in DataFrame that indicates whether an element is an NA value.

See also:

DataFrame.isnull Alias of isna.

DataFrame.notna Boolean inverse of isna.

DataFrame.dropna Omit axes labels with missing values.

isna Top-level isna.

Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.isna()
     age   born   name    toy
0  False   True  False   True
1  False  False  False  False
2   True  False  False  False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0    False
```

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```
1    False
2     True
dtype: bool
```

pandas.DataFrame.isnull

DataFrame.**isnull**()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or `numpy.NaN`, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

Returns

DataFrame Mask of bool values for each element in DataFrame that indicates whether an element is an NA value.

See also:

DataFrame.isnull Alias of isna.

DataFrame.notna Boolean inverse of isna.

DataFrame.dropna Omit axes labels with missing values.

isna Top-level isna.

Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.isna()
     age   born   name    toy
0  False   True  False   True
1  False  False  False  False
2   True  False  False  False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
```

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```
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0    False
1    False
2     True
dtype: bool
```

pandas.DataFrame.items

DataFrame.**items**()

Iterate over (column name, Series) pairs.

Iterates over the DataFrame columns, returning a tuple with the column name and the content as a Series.

Yields

label [object] The column names for the DataFrame being iterated over.

content [Series] The column entries belonging to each label, as a Series.

See also:

DataFrame.iterrows Iterate over DataFrame rows as (index, Series) pairs.

DataFrame.itertuples Iterate over DataFrame rows as namedtuples of the values.

Examples

```
>>> df = pd.DataFrame({'species': ['bear', 'bear', 'marsupial'],
...                    'population': [1864, 22000, 80000]},
...                    index=['panda', 'polar', 'koala'])
>>> df
        species   population
panda   bear      1864
polar   bear      22000
koala   marsupial 80000
>>> for label, content in df.items():
...     print(f'label: {label}')
...     print(f'content: {content}', sep='\n')
...
label: species
content:
panda         bear
polar         bear
koala    marsupial
Name: species, dtype: object
label: population
content:
panda     1864
polar    22000
koala    80000
Name: population, dtype: int64
```

pandas.DataFrame.iteritems

DataFrame.**iteritems**()

Iterate over (column name, Series) pairs.

Iterates over the DataFrame columns, returning a tuple with the column name and the content as a Series.

Yields

label [object] The column names for the DataFrame being iterated over.

content [Series] The column entries belonging to each label, as a Series.

See also:

DataFrame.iterrows Iterate over DataFrame rows as (index, Series) pairs.

DataFrame.itertuples Iterate over DataFrame rows as namedtuples of the values.

Examples

```
>>> df = pd.DataFrame({'species': ['bear', 'bear', 'marsupial'],
...                    'population': [1864, 22000, 80000]},
...                    index=['panda', 'polar', 'koala'])
>>> df
        species   population
panda   bear      1864
polar   bear      22000
koala   marsupial 80000
>>> for label, content in df.items():
...     print(f'label: {label}')
...     print(f'content: {content}', sep='\n')
...
label: species
content:
panda         bear
polar         bear
koala    marsupial
Name: species, dtype: object
label: population
content:
panda     1864
polar    22000
koala    80000
Name: population, dtype: int64
```

pandas.DataFrame.iterrows

DataFrame.**iterrows**()

Iterate over DataFrame rows as (index, Series) pairs.

Yields

index [label or tuple of label] The index of the row. A tuple for a *MultiIndex*.

data [Series] The data of the row as a Series.

See also:

DataFrame.itertuples Iterate over DataFrame rows as namedtuples of the values.

DataFrame.items Iterate over (column name, Series) pairs.

Notes

1. Because `iterrows` returns a Series for each row, it does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
>>> df = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])
>>> row = next(df.iterrows())[1]
>>> row
int      1.0
float    1.5
Name: 0, dtype: float64
>>> print(row['int'].dtype)
float64
>>> print(df['int'].dtype)
int64
```

   To preserve dtypes while iterating over the rows, it is better to use *itertuples()* which returns namedtuples of the values and which is generally faster than `iterrows`.

2. You should **never modify** something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect.

pandas.DataFrame.itertuples

`DataFrame.`**`itertuples`**(*index=True*, *name='Pandas'*)

Iterate over DataFrame rows as namedtuples.

Parameters

index [bool, default True] If True, return the index as the first element of the tuple.

name [str or None, default "Pandas"] The name of the returned namedtuples or None to return regular tuples.

Returns

iterator An object to iterate over namedtuples for each row in the DataFrame with the first field possibly being the index and following fields being the column values.

See also:

DataFrame.iterrows Iterate over DataFrame rows as (index, Series) pairs.

DataFrame.items Iterate over (column name, Series) pairs.

Notes

The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. On python versions < 3.7 regular tuples are returned for DataFrames with a large number of columns (>254).

Examples

```
>>> df = pd.DataFrame({'num_legs': [4, 2], 'num_wings': [0, 2]},
...                   index=['dog', 'hawk'])
>>> df
      num_legs  num_wings
dog          4          0
hawk         2          2
>>> for row in df.itertuples():
...     print(row)
...
Pandas(Index='dog', num_legs=4, num_wings=0)
Pandas(Index='hawk', num_legs=2, num_wings=2)
```

By setting the *index* parameter to False we can remove the index as the first element of the tuple:

```
>>> for row in df.itertuples(index=False):
...     print(row)
...
Pandas(num_legs=4, num_wings=0)
Pandas(num_legs=2, num_wings=2)
```

With the *name* parameter set we set a custom name for the yielded namedtuples:

```
>>> for row in df.itertuples(name='Animal'):
...     print(row)
...
Animal(Index='dog', num_legs=4, num_wings=0)
Animal(Index='hawk', num_legs=2, num_wings=2)
```

pandas.DataFrame.join

DataFrame.**join**(*other*, *on=None*, *how='left'*, *lsuffix=''*, *rsuffix=''*, *sort=False*)

Join columns of another DataFrame.

Join columns with *other* DataFrame either on index or on a key column. Efficiently join multiple DataFrame objects by index at once by passing a list.

Parameters

other [DataFrame, Series, or list of DataFrame] Index should be similar to one of the columns in this one. If a Series is passed, its name attribute must be set, and that will be used as the column name in the resulting joined DataFrame.

on [str, list of str, or array-like, optional] Column or index level name(s) in the caller to join on the index in *other*, otherwise joins index-on-index. If multiple values given, the *other* DataFrame must have a MultiIndex. Can pass an array as the join key if it is not already contained in the calling DataFrame. Like an Excel VLOOKUP operation.

how [{'left', 'right', 'outer', 'inner'}, default 'left'] How to handle the operation of the two objects.

- left: use calling frame's index (or column if on is specified)
- right: use *other*'s index.
- outer: form union of calling frame's index (or column if on is specified) with *other*'s index, and sort it. lexicographically.
- inner: form intersection of calling frame's index (or column if on is specified) with *other*'s index, preserving the order of the calling's one.

lsuffix [str, default ''] Suffix to use from left frame's overlapping columns.

rsuffix [str, default ''] Suffix to use from right frame's overlapping columns.

sort [bool, default False] Order result DataFrame lexicographically by the join key. If False, the order of the join key depends on the join type (how keyword).

Returns

DataFrame A dataframe containing columns from both the caller and *other*.

See also:

DataFrame.merge For column(s)-on-column(s) operations.

Notes

Parameters *on*, *lsuffix*, and *rsuffix* are not supported when passing a list of *DataFrame* objects.

Support for specifying index levels as the *on* parameter was added in version 0.23.0.

Examples

```
>>> df = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3', 'K4', 'K5'],
...                    'A': ['A0', 'A1', 'A2', 'A3', 'A4', 'A5']})
```

```
>>> df
  key   A
0  K0  A0
1  K1  A1
2  K2  A2
3  K3  A3
4  K4  A4
5  K5  A5
```

```
>>> other = pd.DataFrame({'key': ['K0', 'K1', 'K2'],
...                       'B': ['B0', 'B1', 'B2']})
```

```
>>> other
  key   B
0  K0  B0
1  K1  B1
2  K2  B2
```

Join DataFrames using their indexes.

```
>>> df.join(other, lsuffix='_caller', rsuffix='_other')
  key_caller   A key_other    B
0         K0  A0         K0   B0
1         K1  A1         K1   B1
2         K2  A2         K2   B2
3         K3  A3        NaN  NaN
4         K4  A4        NaN  NaN
5         K5  A5        NaN  NaN
```

If we want to join using the key columns, we need to set key to be the index in both *df* and *other*. The joined DataFrame will have key as its index.

```
>>> df.set_index('key').join(other.set_index('key'))
      A    B
key
K0   A0   B0
K1   A1   B1
K2   A2   B2
K3   A3  NaN
K4   A4  NaN
K5   A5  NaN
```

Another option to join using the key columns is to use the *on* parameter. DataFrame.join always uses *other*'s index but we can use any column in *df*. This method preserves the original DataFrame's index in the result.

```
>>> df.join(other.set_index('key'), on='key')
  key   A    B
0  K0  A0   B0
1  K1  A1   B1
2  K2  A2   B2
3  K3  A3  NaN
4  K4  A4  NaN
5  K5  A5  NaN
```

pandas.DataFrame.keys

DataFrame.**keys**()

Get the 'info axis' (see Indexing for more).

This is index for Series, columns for DataFrame.

Returns

Index Info axis.

pandas.DataFrame.kurt

DataFrame.**kurt**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.kurtosis

DataFrame.**kurtosis**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.last

DataFrame.**last**(*offset*)

Select final periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the last few rows based on a date offset.

Parameters

offset [str, DateOffset, dateutil.relativedelta] The offset length of the data that will be selected. For instance, '3D' will display all the rows having their index within the last 3 days.

Returns

Series or DataFrame A subset of the caller.

Raises

TypeError If the index is not a *DatetimeIndex*

See also:

first Select initial periods of time series based on a date offset.

at_time Select values at a particular time of the day.

between_time Select values between particular times of the day.

Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
            A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the last 3 days:

```
>>> ts.last('3D')
            A
2018-04-13  3
2018-04-15  4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

pandas.DataFrame.last_valid_index

DataFrame.**last_valid_index**()

Return index for last non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

pandas.DataFrame.le

DataFrame.**le**(*other*, *axis='columns'*, *level=None*)

Get Less than or equal to of dataframe and other, element-wise (binary operator *le*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to ==, *!*=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.

DataFrame.ne Compare DataFrames for inequality elementwise.

DataFrame.le Compare DataFrames for less than inequality or equality elementwise.

DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.

DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.

DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. *NaN* values are considered different (i.e. *NaN* != *NaN*).

Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost  revenue
A   250      100
B   150      250
C   100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
    cost  revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
    cost  revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
    cost  revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
    cost  revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
   revenue
A      300
B      250
C      100
D      150
```

```
>>> df.gt(other)
    cost  revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                              'revenue': [100, 250, 300, 200, 175, 225]},
...                             index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                    ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost  revenue
Q1 A   250      100
   B   150      250
   C   100      300
Q2 A   150      200
   B   300      175
   C   220      225
```

```
>>> df.le(df_multindex, level=1)
       cost  revenue
Q1 A   True     True
   B   True     True
   C   True     True
Q2 A  False     True
   B   True    False
   C   True    False
```

pandas.DataFrame.lookup

DataFrame.**lookup**(*row_labels*, *col_labels*)

Label-based "fancy indexing" function for DataFrame. Given equal-length arrays of row and column labels, return an array of the values corresponding to each (row, col) pair.

Deprecated since version 1.2.0: DataFrame.lookup is deprecated, use DataFrame.melt and DataFrame.loc instead. For an example see *lookup()* in the user guide.

Parameters

row_labels [sequence] The row labels to use for lookup.

col_labels [sequence] The column labels to use for lookup.

Returns

numpy.ndarray The found values.

pandas.DataFrame.lt

DataFrame.**lt**(*other*, *axis='columns'*, *level=None*)

Get Less than of dataframe and other, element-wise (binary operator *lt*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to ==, *!*=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.

DataFrame.ne Compare DataFrames for inequality elementwise.

DataFrame.le Compare DataFrames for less than inequality or equality elementwise.

DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.

DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.

DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. *NaN* values are considered different (i.e. *NaN* != *NaN*).

Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost  revenue
A   250      100
B   150      250
C   100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
    cost  revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
    cost  revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
    cost  revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
    cost  revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
   revenue
A      300
B      250
C      100
D      150
```

```
>>> df.gt(other)
    cost  revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                              'revenue': [100, 250, 300, 200, 175, 225]},
...                             index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                    ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost  revenue
Q1 A   250      100
   B   150      250
   C   100      300
Q2 A   150      200
   B   300      175
   C   220      225
```

```
>>> df.le(df_multindex, level=1)
       cost  revenue
Q1 A   True     True
   B   True     True
   C   True     True
Q2 A  False     True
   B   True    False
   C   True    False
```

pandas.DataFrame.mad

DataFrame.**mad**(*axis=None*, *skipna=None*, *level=None*)

Return the mean absolute deviation of the values over the requested axis.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default None] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.mask

DataFrame.**mask**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *errors='raise'*, *try_cast=False*)

Replace values where the condition is True.

Parameters

cond [bool Series/DataFrame, array-like, or callable] Where *cond* is False, keep the original value. Where True, replace with corresponding value from *other*. If *cond* is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

other [scalar, Series/DataFrame, or callable] Entries where *cond* is True are replaced with corresponding value from *other*. If other is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

inplace [bool, default False] Whether to perform the operation in place on the data.

axis [int, default None] Alignment axis if needed.

level [int, default None] Alignment level if needed.

errors [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won't affect the results and will always coerce to a suitable dtype.

- 'raise' : allow exceptions to be raised.
- 'ignore' : suppress exceptions. On error return original object.

try_cast [bool, default False] Try to cast the result back to the input type (if possible).

Returns

Same type as caller or None if `inplace=True`.

See also:

DataFrame.where() Return an object of same shape as self.

Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if `cond` is `False` the element is used; otherwise the corresponding element from the DataFrame `other` is used.

The signature for *`DataFrame.where()`* differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the `mask` documentation in *indexing*.

Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0
dtype: float64
>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0    10
1    10
2    2
3    3
4    4
dtype: int64
>>> s.mask(s > 1, 10)
0     0
1     1
2    10
3    10
4    10
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
4  8  9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0  0 -1
```

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```
1 -2  3
2 -4 -5
3  6 -7
4 -8  9
>>> df.where(m, -df) == np.where(m, df, -df)
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

pandas.DataFrame.max

DataFrame.**max**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the maximum of the values over the requested axis.

If you want the *index* of the maximum, use `idxmax`. This isthe equivalent of the `numpy.ndarray` method `argmax`.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded  animal
warm     dog       4
         falcon    2
cold     fish      0
         spider    8
Name: legs, dtype: int64
```

```
>>> s.max()
8
```

Max using level names, as well as indices.

```
>>> s.max(level='blooded')
blooded
warm    4
cold    8
Name: legs, dtype: int64
```

```
>>> s.max(level=0)
blooded
warm    4
cold    8
Name: legs, dtype: int64
```

pandas.DataFrame.mean

DataFrame.**mean**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the mean of the values over the requested axis.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.median

DataFrame.**median**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the median of the values over the requested axis.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.melt

DataFrame.**melt**(*id_vars=None*, *value_vars=None*, *var_name=None*, *value_name='value'*, *col_level=None*, *ignore_index=True*)

Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (*id_vars*), while all other columns, considered measured variables (*value_vars*), are "unpivoted" to the row axis, leaving just two non-identifier columns, 'variable' and 'value'.

Parameters

id_vars [tuple, list, or ndarray, optional] Column(s) to use as identifier variables.

value_vars [tuple, list, or ndarray, optional] Column(s) to unpivot. If not specified, uses all columns that are not set as *id_vars*.

var_name [scalar] Name to use for the 'variable' column. If None it uses `frame.columns.name` or 'variable'.

value_name [scalar, default 'value'] Name to use for the 'value' column.

col_level [int or str, optional] If columns are a MultiIndex then use this level to melt.

ignore_index [bool, default True] If True, original index is ignored. If False, the original index is retained. Index labels will be repeated as necessary.

New in version 1.1.0.

Returns

DataFrame Unpivoted DataFrame.

See also:

melt Identical method.

pivot_table Create a spreadsheet-style pivot table as a DataFrame.

DataFrame.pivot Return reshaped DataFrame organized by given index / column values.

DataFrame.explode Explode a DataFrame from list-like columns to long format.

Examples

```
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
...                    'B': {0: 1, 1: 3, 2: 5},
...                    'C': {0: 2, 1: 4, 2: 6}})
>>> df
   A  B  C
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> df.melt(id_vars=['A'], value_vars=['B'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
```

```
>>> df.melt(id_vars=['A'], value_vars=['B', 'C'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
3  a        C      2
4  b        C      4
5  c        C      6
```

The names of 'variable' and 'value' columns can be customized:

```
>>> df.melt(id_vars=['A'], value_vars=['B'],
...         var_name='myVarname', value_name='myValname')
   A myVarname  myValname
0  a         B          1
1  b         B          3
2  c         B          5
```

Original index values can be kept around:

```
>>> df.melt(id_vars=['A'], value_vars=['B', 'C'], ignore_index=False)
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
0  a        C      2
1  b        C      4
2  c        C      6
```

If you have multi-index columns:

```
>>> df.columns = [list('ABC'), list('DEF')]
>>> df
   A  B  C
   D  E  F
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> df.melt(col_level=0, id_vars=['A'], value_vars=['B'])
   A variable  value
0  a        B      1
1  b        B      3
2  c        B      5
```

```
>>> df.melt(id_vars=[('A', 'D')], value_vars=[('B', 'E')])
  (A, D) variable_0 variable_1  value
0      a          B          E      1
1      b          B          E      3
2      c          B          E      5
```

pandas.DataFrame.memory_usage

DataFrame.**memory_usage**(*index=True*, *deep=False*)

Return the memory usage of each column in bytes.

The memory usage can optionally include the contribution of the index and elements of *object* dtype.

This value is displayed in *DataFrame.info* by default. This can be suppressed by setting `pandas.options.display.memory_usage` to False.

Parameters

index [bool, default True] Specifies whether to include the memory usage of the DataFrame's index in returned Series. If `index=True`, the memory usage of the index is the first item in the output.

deep [bool, default False] If True, introspect the data deeply by interrogating *object* dtypes for system-level memory consumption, and include it in the returned values.

Returns

Series A Series whose index is the original column names and whose values is the memory usage of each column in bytes.

See also:

numpy.ndarray.nbytes Total bytes consumed by the elements of an ndarray.

Series.memory_usage Bytes consumed by a Series.

Categorical Memory-efficient array for string values with many repeated values.

DataFrame.info Concise summary of a DataFrame.

Examples

```
>>> dtypes = ['int64', 'float64', 'complex128', 'object', 'bool']
>>> data = dict([(t, np.ones(shape=5000, dtype=int).astype(t))
...              for t in dtypes])
>>> df = pd.DataFrame(data)
>>> df.head()
   int64  float64            complex128  object  bool
0      1      1.0              1.0+0.0j       1  True
1      1      1.0              1.0+0.0j       1  True
2      1      1.0              1.0+0.0j       1  True
3      1      1.0              1.0+0.0j       1  True
4      1      1.0              1.0+0.0j       1  True
```

```
>>> df.memory_usage()
Index           128
int64         40000
float64       40000
complex128    80000
object        40000
bool           5000
dtype: int64
```

```
>>> df.memory_usage(index=False)
int64         40000
float64       40000
complex128    80000
object        40000
bool           5000
dtype: int64
```

The memory footprint of *object* dtype columns is ignored by default:

```
>>> df.memory_usage(deep=True)
Index           128
int64         40000
float64       40000
complex128    80000
object       180000
bool           5000
dtype: int64
```

Use a Categorical for efficient storage of an object-dtype column with many repeated values.

```
>>> df['object'].astype('category').memory_usage(deep=True)
5244
```

pandas.DataFrame.merge

DataFrame.**merge**(*right*, *how='inner'*, *on=None*, *left_on=None*, *right_on=None*, *left_index=False*, *right_index=False*, *sort=False*, *suffixes=('_x', '_y')*, *copy=True*, *indicator=False*, *validate=None*)

Merge DataFrame or named Series objects with a database-style join.

The join is done on columns or indexes. If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on. When performing a cross merge, no column specifications to merge on are allowed.

Parameters

right [DataFrame or named Series] Object to merge with.

how [{'left', 'right', 'outer', 'inner', 'cross'}, default 'inner'] Type of merge to be performed.

- left: use only keys from left frame, similar to a SQL left outer join; preserve key order.
- right: use only keys from right frame, similar to a SQL right outer join; preserve key order.
- outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.
- inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.
- cross: creates the cartesian product from both frames, preserves the order of the left keys.

  New in version 1.2.0.

on [label or list] Column or index level names to join on. These must be found in both DataFrames. If *on* is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.

left_on [label or list, or array-like] Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.

right_on [label or list, or array-like] Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.

left_index [bool, default False] Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels.

right_index [bool, default False] Use the index from the right DataFrame as the join key. Same caveats as left_index.

sort [bool, default False] Sort the join keys lexicographically in the result DataFrame. If False, the order of the join keys depends on the join type (how keyword).

suffixes [list-like, default is ("_x", "_y")] A length-2 sequence where each element is optionally a string indicating the suffix to add to overlapping column names in *left* and *right* respectively. Pass a value of *None* instead of a string to indicate that the column name from *left* or *right* should be left as-is, with no suffix. At least one of the values must not be None.

copy [bool, default True] If False, avoid copy if possible.

indicator [bool or str, default False] If True, adds a column to the output DataFrame called "_merge" with information on the source of each row. The column can be given a different name by providing a string argument. The column will have a Categorical type with the value of "left_only" for observations whose merge key only appears in the left DataFrame, "right_only" for observations whose merge key only appears in the right DataFrame, and "both" if the observation's merge key is found in both DataFrames.

validate [str, optional] If specified, checks if merge is of specified type.

- "one_to_one" or "1:1": check if merge keys are unique in both left and right datasets.
- "one_to_many" or "1:m": check if merge keys are unique in left dataset.
- "many_to_one" or "m:1": check if merge keys are unique in right dataset.
- "many_to_many" or "m:m": allowed, but does not result in checks.

Returns

DataFrame A DataFrame of the two merged objects.

See also:

merge_ordered Merge with optional filling/interpolation.

merge_asof Merge on nearest keys.

DataFrame.join Similar method using indices.

Notes

Support for specifying index levels as the *on*, *left_on*, and *right_on* parameters was added in version 0.23.0
Support for merging named Series objects was added in version 0.24.0

Examples

```
>>> df1 = pd.DataFrame({'lkey': ['foo', 'bar', 'baz', 'foo'],
...                     'value': [1, 2, 3, 5]})
>>> df2 = pd.DataFrame({'rkey': ['foo', 'bar', 'baz', 'foo'],
...                     'value': [5, 6, 7, 8]})
>>> df1
    lkey value
0   foo      1
1   bar      2
2   baz      3
3   foo      5
>>> df2
    rkey value
0   foo      5
1   bar      6
2   baz      7
3   foo      8
```

Merge df1 and df2 on the lkey and rkey columns. The value columns have the default suffixes, _x and _y, appended.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey')
  lkey  value_x rkey  value_y
0  foo        1  foo        5
1  foo        1  foo        8
2  foo        5  foo        5
3  foo        5  foo        8
4  bar        2  bar        6
5  baz        3  baz        7
```

Merge DataFrames df1 and df2 with specified left and right suffixes appended to any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey',
...           suffixes=('_left', '_right'))
  lkey  value_left rkey  value_right
0  foo           1  foo            5
1  foo           1  foo            8
2  foo           5  foo            5
3  foo           5  foo            8
4  bar           2  bar            6
5  baz           3  baz            7
```

Merge DataFrames df1 and df2, but raise an exception if the DataFrames have any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey', suffixes=(False, False))
Traceback (most recent call last):
...
ValueError: columns overlap but no suffix specified:
    Index(['value'], dtype='object')
```

```
>>> df1 = pd.DataFrame({'a': ['foo', 'bar'], 'b': [1, 2]})
>>> df2 = pd.DataFrame({'a': ['foo', 'baz'], 'c': [3, 4]})
>>> df1
      a  b
0   foo  1
1   bar  2
>>> df2
      a  c
0   foo  3
1   baz  4
```

```
>>> df1.merge(df2, how='inner', on='a')
      a  b  c
0   foo  1  3
```

```
>>> df1.merge(df2, how='left', on='a')
      a  b  c
0   foo  1  3.0
1   bar  2  NaN
```

```
>>> df1 = pd.DataFrame({'left': ['foo', 'bar']})
>>> df2 = pd.DataFrame({'right': [7, 8]})
>>> df1
    left
0   foo
1   bar
>>> df2
```

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```
    right
0   7
1   8
```

```
>>> df1.merge(df2, how='cross')
   left  right
0   foo      7
1   foo      8
2   bar      7
3   bar      8
```

pandas.DataFrame.min

DataFrame.**min**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the minimum of the values over the requested axis.

If you want the *index* of the minimum, use `idxmin`. This isthe equivalent of the `numpy.ndarray` method `argmin`.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded  animal
warm     dog       4
         falcon    2
cold     fish      0
         spider    8
Name: legs, dtype: int64
```

```
>>> s.min()
0
```

Min using level names, as well as indices.

```
>>> s.min(level='blooded')
blooded
warm    2
cold    0
Name: legs, dtype: int64
```

```
>>> s.min(level=0)
blooded
warm    2
cold    0
Name: legs, dtype: int64
```

pandas.DataFrame.mod

DataFrame.**mod**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Modulo of dataframe and other, element-wise (binary operator *mod*).

Equivalent to `dataframe % other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rmod*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
```

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```
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.mode

DataFrame.**mode**(*axis=0*, *numeric_only=False*, *dropna=True*)

Get the mode(s) of each element along the selected axis.

The mode of a set of values is the value that appears most often. It can be multiple values.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to iterate over while searching for the mode:

- 0 or 'index' : get mode of each column
- 1 or 'columns' : get mode of each row.

numeric_only [bool, default False] If True, only apply to numeric columns.

dropna [bool, default True] Don't consider counts of NaN/NaT.

New in version 0.24.0.

Returns

DataFrame The modes of each column or row.

See also:

Series.mode Return the highest frequency value in a Series.

Series.value_counts Return the counts of values in a Series.

Examples

```
>>> df = pd.DataFrame([('bird', 2, 2),
...                    ('mammal', 4, np.nan),
...                    ('arthropod', 8, 0),
...                    ('bird', 2, np.nan)],
...                   index=('falcon', 'horse', 'spider', 'ostrich'),
...                   columns=('species', 'legs', 'wings'))
>>> df
           species  legs  wings
falcon        bird     2    2.0
horse       mammal     4    NaN
spider   arthropod     8    0.0
ostrich       bird     2    NaN
```

By default, missing values are not considered, and the mode of wings are both 0 and 2. Because the resulting DataFrame has two rows, the second row of `species` and `legs` contains `NaN`.

```
>>> df.mode()
  species  legs  wings
0    bird   2.0    0.0
1     NaN   NaN    2.0
```

Setting `dropna=False` `NaN` values are considered and they can be the mode (like for wings).

```
>>> df.mode(dropna=False)
  species  legs  wings
0    bird     2    NaN
```

Setting `numeric_only=True`, only the mode of numeric columns is computed, and columns of other types are ignored.

```
>>> df.mode(numeric_only=True)
   legs  wings
0   2.0    0.0
1   NaN    2.0
```

To compute the mode over columns and not rows, use the axis parameter:

```
>>> df.mode(axis='columns', numeric_only=True)
           0    1
falcon   2.0  NaN
horse    4.0  NaN
spider   0.0  8.0
ostrich  2.0  NaN
```

pandas.DataFrame.mul

`DataFrame.`**`mul`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Multiplication of dataframe and other, element-wise (binary operator *mul*).

Equivalent to `dataframe * other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rmul*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.multiply

DataFrame.**multiply**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Multiplication of dataframe and other, element-wise (binary operator *mul*).

Equivalent to `dataframe * other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rmul*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
```

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```
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.ne

DataFrame.**ne**(*other*, *axis='columns'*, *level=None*)

Get Not equal to of dataframe and other, element-wise (binary operator *ne*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to ==, *!*=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.

DataFrame.ne Compare DataFrames for inequality elementwise.

DataFrame.le Compare DataFrames for less than inequality or equality elementwise.

DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.

DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.

DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. *NaN* values are considered different (i.e. *NaN* != *NaN*).

Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost  revenue
A   250      100
B   150      250
C   100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
    cost  revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
    cost  revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
    cost  revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
    cost  revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
   revenue
A      300
B      250
C      100
D      150
```

```
>>> df.gt(other)
    cost  revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                              'revenue': [100, 250, 300, 200, 175, 225]},
...                             index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                    ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost  revenue
Q1 A   250      100
   B   150      250
   C   100      300
Q2 A   150      200
   B   300      175
   C   220      225
```

```
>>> df.le(df_multindex, level=1)
       cost  revenue
Q1 A   True     True
   B   True     True
   C   True     True
Q2 A  False     True
   B   True    False
   C   True    False
```

pandas.DataFrame.nlargest

DataFrame.**nlargest**(*n*, *columns*, *keep='first'*)

Return the first *n* rows ordered by *columns* in descending order.

Return the first *n* rows with the largest values in *columns*, in descending order. The columns that are not specified are returned as well, but not used for ordering.

This method is equivalent to `df.sort_values(columns, ascending=False).head(n)`, but more performant.

Parameters

n [int] Number of rows to return.

columns [label or list of labels] Column label(s) to order by.

keep [{'first', 'last', 'all'}, default 'first'] Where there are duplicate values:

- *first* : prioritize the first occurrence(s)
- *last* : prioritize the last occurrence(s)
- **all** [do not drop any duplicates, even it means] selecting more than *n* items.

New in version 0.24.0.

Returns

DataFrame The first *n* rows ordered by the given columns in descending order.

See also:

DataFrame.nsmallest Return the first *n* rows ordered by *columns* in ascending order.

DataFrame.sort_values Sort DataFrame by the values.

DataFrame.head Return the first *n* rows without re-ordering.

Notes

This function cannot be used with all column types. For example, when specifying columns with *object* or *category* dtypes, `TypeError` is raised.

Examples

```
>>> df = pd.DataFrame({'population': [59000000, 65000000, 434000,
...                                   434000, 434000, 337000, 11300,
...                                   11300, 11300],
...                    'GDP': [1937894, 2583560 , 12011, 4520, 12128,
...                            17036, 182, 38, 311],
...                    'alpha-2': ["IT", "FR", "MT", "MV", "BN",
...                                "IS", "NR", "TV", "AI"]},
...                   index=["Italy", "France", "Malta",
...                          "Maldives", "Brunei", "Iceland",
...                          "Nauru", "Tuvalu", "Anguilla"])
>>> df
          population      GDP alpha-2
Italy       59000000  1937894      IT
France      65000000  2583560      FR
```

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```
Malta          434000    12011      MT
Maldives       434000     4520      MV
Brunei         434000    12128      BN
Iceland        337000    17036      IS
Nauru           11300      182      NR
Tuvalu          11300       38      TV
Anguilla        11300      311      AI
```

In the following example, we will use `nlargest` to select the three rows having the largest values in column "population".

```
>>> df.nlargest(3, 'population')
        population      GDP alpha-2
France    65000000  2583560      FR
Italy     59000000  1937894      IT
Malta       434000    12011      MT
```

When using `keep='last'`, ties are resolved in reverse order:

```
>>> df.nlargest(3, 'population', keep='last')
        population      GDP alpha-2
France    65000000  2583560      FR
Italy     59000000  1937894      IT
Brunei      434000    12128      BN
```

When using `keep='all'`, all duplicate items are maintained:

```
>>> df.nlargest(3, 'population', keep='all')
          population      GDP alpha-2
France      65000000  2583560      FR
Italy       59000000  1937894      IT
Malta         434000    12011      MT
Maldives      434000     4520      MV
Brunei        434000    12128      BN
```

To order by the largest values in column "population" and then "GDP", we can specify multiple columns like in the next example.

```
>>> df.nlargest(3, ['population', 'GDP'])
        population      GDP alpha-2
France    65000000  2583560      FR
Italy     59000000  1937894      IT
Brunei      434000    12128      BN
```

pandas.DataFrame.notna

DataFrame.**notna**()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or `numpy.NaN`, get mapped to False values.

Returns

DataFrame Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

See also:

DataFrame.notnull Alias of notna.

DataFrame.isna Boolean inverse of notna.

DataFrame.dropna Omit axes labels with missing values.

notna Top-level notna.

Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.notna()
     age   born  name    toy
0   True  False  True  False
1   True   True  True   True
2  False   True  True   True
```

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0     True
1     True
2    False
dtype: bool
```

pandas.DataFrame.notnull

DataFrame.**notnull**()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or `numpy.NaN`, get mapped to False values.

Returns

DataFrame Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

See also:

DataFrame.notnull Alias of notna.

DataFrame.isna Boolean inverse of notna.

DataFrame.dropna Omit axes labels with missing values.

notna Top-level notna.

Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame(dict(age=[5, 6, np.NaN],
...                        born=[pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                        name=['Alfred', 'Batman', ''],
...                        toy=[None, 'Batmobile', 'Joker']))
>>> df
   age       born    name        toy
0  5.0        NaT  Alfred       None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25              Joker
```

```
>>> df.notna()
     age   born  name    toy
0   True  False  True  False
1   True   True  True   True
2  False   True  True   True
```

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0     True
```

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```
1     True
2    False
dtype: bool
```

pandas.DataFrame.nsmallest

DataFrame.**nsmallest**(*n*, *columns*, *keep='first'*)

Return the first *n* rows ordered by *columns* in ascending order.

Return the first *n* rows with the smallest values in *columns*, in ascending order. The columns that are not specified are returned as well, but not used for ordering.

This method is equivalent to `df.sort_values(columns, ascending=True).head(n)`, but more performant.

Parameters

n [int] Number of items to retrieve.

columns [list or str] Column name or names to order by.

keep [{'first', 'last', 'all'}, default 'first'] Where there are duplicate values:

- `first` : take the first occurrence.
- `last` : take the last occurrence.
- `all` : do not drop any duplicates, even it means selecting more than *n* items.

New in version 0.24.0.

Returns

DataFrame

See also:

DataFrame.nlargest Return the first *n* rows ordered by *columns* in descending order.

DataFrame.sort_values Sort DataFrame by the values.

DataFrame.head Return the first *n* rows without re-ordering.

Examples

```
>>> df = pd.DataFrame({'population': [59000000, 65000000, 434000,
...                                   434000, 434000, 337000, 337000,
...                                   11300, 11300],
...                    'GDP': [1937894, 2583560 , 12011, 4520, 12128,
...                            17036, 182, 38, 311],
...                    'alpha-2': ["IT", "FR", "MT", "MV", "BN",
...                                "IS", "NR", "TV", "AI"]},
...                   index=["Italy", "France", "Malta",
...                          "Maldives", "Brunei", "Iceland",
...                          "Nauru", "Tuvalu", "Anguilla"])
>>> df
          population      GDP alpha-2
Italy       59000000  1937894      IT
```

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```
France      65000000  2583560      FR
Malta         434000    12011      MT
Maldives      434000     4520      MV
Brunei        434000    12128      BN
Iceland       337000    17036      IS
Nauru         337000      182      NR
Tuvalu         11300       38      TV
Anguilla       11300      311      AI
```

In the following example, we will use `nsmallest` to select the three rows having the smallest values in column "population".

```
>>> df.nsmallest(3, 'population')
          population    GDP alpha-2
Tuvalu         11300     38      TV
Anguilla       11300    311      AI
Iceland       337000  17036      IS
```

When using `keep='last'`, ties are resolved in reverse order:

```
>>> df.nsmallest(3, 'population', keep='last')
          population  GDP alpha-2
Anguilla       11300  311      AI
Tuvalu         11300   38      TV
Nauru         337000  182      NR
```

When using `keep='all'`, all duplicate items are maintained:

```
>>> df.nsmallest(3, 'population', keep='all')
          population    GDP alpha-2
Tuvalu         11300     38      TV
Anguilla       11300    311      AI
Iceland       337000  17036      IS
Nauru         337000    182      NR
```

To order by the smallest values in column "population" and then "GDP", we can specify multiple columns like in the next example.

```
>>> df.nsmallest(3, ['population', 'GDP'])
          population  GDP alpha-2
Tuvalu         11300   38      TV
Anguilla       11300  311      AI
Nauru         337000  182      NR
```

pandas.DataFrame.nunique

`DataFrame.`**`nunique`**(*axis=0*, *dropna=True*)

Count distinct observations over requested axis.

Return Series with number of distinct observations. Can ignore NaN values.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

dropna [bool, default True] Don't include NaN in the counts.

Returns

Series

See also:

Series.nunique Method nunique for Series.

DataFrame.count Count non-NA cells for each column or row.

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [1, 1, 1]})
>>> df.nunique()
A    3
B    1
dtype: int64
```

```
>>> df.nunique(axis=1)
0    1
1    2
2    2
dtype: int64
```

pandas.DataFrame.pad

DataFrame.**pad**(*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for *DataFrame.fillna()* with `method='ffill'`.

Returns

{klass} or None Object with missing values filled or None if `inplace=True`.

pandas.DataFrame.pct_change

DataFrame.**pct_change**(*periods=1*, *fill_method='pad'*, *limit=None*, *freq=None*, ***kwargs*)

Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

Parameters

periods [int, default 1] Periods to shift for forming percent change.

fill_method [str, default 'pad'] How to handle NAs before computing percent changes.

limit [int, default None] The number of consecutive NAs to fill before stopping.

freq [DateOffset, timedelta, or str, optional] Increment to use from time series API (e.g. 'M' or BDay()).

****kwargs** Additional keyword arguments are passed into *DataFrame.shift* or *Series.shift*.

Returns

chg [Series or DataFrame] The same type as the calling object.

See also:

Series.diff Compute the difference of two elements in a Series.

DataFrame.diff Compute the difference of two elements in a DataFrame.

Series.shift Shift the index by some number of periods.

DataFrame.shift Shift the index by some number of periods.

Examples

Series

```
>>> s = pd.Series([90, 91, 85])
>>> s
0    90
1    91
2    85
dtype: int64
```

```
>>> s.pct_change()
0         NaN
1    0.011111
2   -0.065934
dtype: float64
```

```
>>> s.pct_change(periods=2)
0         NaN
1         NaN
2   -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

```
>>> s = pd.Series([90, 91, None, 85])
>>> s
0    90.0
1    91.0
2     NaN
3    85.0
dtype: float64
```

```
>>> s.pct_change(fill_method='ffill')
0         NaN
1    0.011111
2    0.000000
3   -0.065934
dtype: float64
```

DataFrame

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

```
>>> df = pd.DataFrame({
...     'FR': [4.0405, 4.0963, 4.3149],
...     'GR': [1.7246, 1.7482, 1.8519],
```

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```
...      'IT': [804.74, 810.01, 860.13]},
...      index=['1980-01-01', '1980-02-01', '1980-03-01'])
>>> df
                FR      GR      IT
1980-01-01  4.0405  1.7246  804.74
1980-02-01  4.0963  1.7482  810.01
1980-03-01  4.3149  1.8519  860.13
```

```
>>> df.pct_change()
                  FR        GR        IT
1980-01-01       NaN       NaN       NaN
1980-02-01  0.013810  0.013684  0.006549
1980-03-01  0.053365  0.059318  0.061876
```

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

```
>>> df = pd.DataFrame({
...      '2016': [1769950, 30586265],
...      '2015': [1500923, 40912316],
...      '2014': [1371819, 41403351]},
...      index=['GOOG', 'APPL'])
>>> df
          2016      2015      2014
GOOG   1769950   1500923   1371819
APPL  30586265  40912316  41403351
```

```
>>> df.pct_change(axis='columns')
      2016      2015      2014
GOOG   NaN -0.151997 -0.086016
APPL   NaN  0.337604  0.012002
```

pandas.DataFrame.pipe

DataFrame.**pipe**(*func*, **args*, ***kwargs*)

Apply func(self, *args, **kwargs).

Parameters

func [function] Function to apply to the Series/DataFrame. `args`, and `kwargs` are passed into `func`. Alternatively a `(callable, data_keyword)` tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the Series/DataFrame.

args [iterable, optional] Positional arguments passed into `func`.

kwargs [mapping, optional] A dictionary of keyword arguments passed into `func`.

Returns

object [the return type of `func`.]

See also:

DataFrame.apply Apply a function along input axis of DataFrame.

DataFrame.applymap Apply a function elementwise on a whole DataFrame.

Series.map Apply a mapping correspondence on a *Series*.

Notes

Use `.pipe` when chaining together functions that expect Series, DataFrames or GroupBy objects. Instead of writing

```
>>> func(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe(func, arg2=b, arg3=c)
... )
```

If you have a function that takes the data as (say) the second argument, pass a tuple indicating which keyword expects the data. For example, suppose `f` takes its data as `arg2`:

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe((func, 'arg2'), arg1=a, arg3=c)
...  )
```

pandas.DataFrame.pivot

DataFrame.**pivot**(*index=None*, *columns=None*, *values=None*)

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a "pivot" table) based on column values. Uses unique values from specified *index* / *columns* to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the *User Guide* for more on reshaping.

Parameters

index [str or object or a list of str, optional] Column to use to make new frame's index. If None, uses existing index.

Changed in version 1.1.0: Also accept list of index names.

columns [str or object or a list of str] Column to use to make new frame's columns.

Changed in version 1.1.0: Also accept list of columns names.

values [str, object or a list of the previous, optional] Column(s) to use for populating new frame's values. If not specified, all remaining columns will be used and the result will have hierarchically indexed columns.

Returns

DataFrame Returns reshaped DataFrame.

Raises

ValueError: When there are any *index*, *columns* combinations with multiple values. *DataFrame.pivot_table* when you need to aggregate.

See also:

DataFrame.pivot_table Generalization of pivot that can handle duplicate values for one index/column pair.

DataFrame.unstack Pivot based on the index values instead of a column.

wide_to_long Wide panel to long format. Less flexible but more user-friendly than melt.

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods.

Examples

```
>>> df = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two',
...                            'two'],
...                    'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
...                    'baz': [1, 2, 3, 4, 5, 6],
...                    'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
>>> df
    foo   bar  baz  zoo
0   one   A    1    x
1   one   B    2    y
2   one   C    3    z
3   two   A    4    q
4   two   B    5    w
5   two   C    6    t
```

```
>>> df.pivot(index='foo', columns='bar', values='baz')
bar  A   B   C
foo
one  1   2   3
two  4   5   6
```

```
>>> df.pivot(index='foo', columns='bar')['baz']
bar  A   B   C
foo
one  1   2   3
two  4   5   6
```

```
>>> df.pivot(index='foo', columns='bar', values=['baz', 'zoo'])
      baz       zoo
bar   A  B  C   A  B  C
foo
one   1  2  3   x  y  z
two   4  5  6   q  w  t
```

You could also assign a list of column names or a list of index names.

```
>>> df = pd.DataFrame({
...        "lev1": [1, 1, 1, 2, 2, 2],
...        "lev2": [1, 1, 2, 1, 1, 2],
...        "lev3": [1, 2, 1, 2, 1, 2],
...        "lev4": [1, 2, 3, 4, 5, 6],
...        "values": [0, 1, 2, 3, 4, 5]})
```

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```
>>> df
    lev1 lev2 lev3 lev4 values
0   1    1    1    1    0
1   1    1    2    2    1
2   1    2    1    3    2
3   2    1    2    4    3
4   2    1    1    5    4
5   2    2    2    6    5
```

```
>>> df.pivot(index="lev1", columns=["lev2", "lev3"],values="values")
lev2    1          2
lev3    1    2     1    2
lev1
1     0.0  1.0   2.0  NaN
2     4.0  3.0   NaN  5.0
```

```
>>> df.pivot(index=["lev1", "lev2"], columns=["lev3"],values="values")
      lev3    1    2
lev1  lev2
   1     1  0.0  1.0
         2  2.0  NaN
   2     1  4.0  3.0
         2  NaN  5.0
```

A ValueError is raised if there are any duplicates.

```
>>> df = pd.DataFrame({"foo": ['one', 'one', 'two', 'two'],
...                    "bar": ['A', 'A', 'B', 'C'],
...                    "baz": [1, 2, 3, 4]})
>>> df
   foo bar  baz
0  one   A    1
1  one   A    2
2  two   B    3
3  two   C    4
```

Notice that the first two rows are the same for our *index* and *columns* arguments.

```
>>> df.pivot(index='foo', columns='bar', values='baz')
Traceback (most recent call last):
   ...
ValueError: Index contains duplicate entries, cannot reshape
```

pandas.DataFrame.pivot_table

DataFrame.**pivot_table**(*values=None*, *index=None*, *columns=None*, *aggfunc='mean'*, *fill_value=None*, *margins=False*, *dropna=True*, *margins_name='All'*, *observed=False*)

Create a spreadsheet-style pivot table as a DataFrame.

The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame.

Parameters

values [column to aggregate, optional]

index [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc [function, list of functions, dict, default numpy.mean] If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions.

fill_value [scalar, default None] Value to replace missing values with (in the resulting pivot table, after aggregation).

margins [bool, default False] Add all row / columns (e.g. for subtotal / grand totals).

dropna [bool, default True] Do not include columns whose entries are all NaN.

margins_name [str, default 'All'] Name of the row / column that will contain the totals when margins is True.

observed [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

Changed in version 0.25.0.

Returns

DataFrame An Excel style pivot table.

See also:

DataFrame.pivot Pivot without aggregation that can handle non-numeric data.

DataFrame.melt Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

wide_to_long Wide panel to long format. Less flexible but more user-friendly than melt.

Examples

```
>>> df = pd.DataFrame({"A": ["foo", "foo", "foo", "foo", "foo",
...                          "bar", "bar", "bar", "bar"],
...                    "B": ["one", "one", "one", "two", "two",
...                          "one", "one", "two", "two"],
...                    "C": ["small", "large", "large", "small",
...                          "small", "large", "small", "small",
...                          "large"],
...                    "D": [1, 2, 2, 3, 3, 4, 5, 6, 7],
...                    "E": [2, 4, 5, 5, 6, 6, 8, 9, 9]})
>>> df
     A    B      C  D  E
0  foo  one  small  1  2
1  foo  one  large  2  4
2  foo  one  large  2  5
3  foo  two  small  3  5
```

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```
4  foo  two  small  3  6
5  bar  one  large  4  6
6  bar  one  small  5  8
7  bar  two  small  6  9
8  bar  two  large  7  9
```

This first example aggregates values by taking the sum.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                        columns=['C'], aggfunc=np.sum)
>>> table
C        large  small
A   B
bar one    4.0    5.0
    two    7.0    6.0
foo one    4.0    1.0
    two    NaN    6.0
```

We can also fill missing values using the *fill_value* parameter.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                        columns=['C'], aggfunc=np.sum, fill_value=0)
>>> table
C        large  small
A   B
bar one      4      5
    two      7      6
foo one      4      1
    two      0      6
```

The next example aggregates by taking the mean across multiple columns.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                        aggfunc={'D': np.mean,
...                                 'E': np.mean})
>>> table
                D         E
A   C
bar large  5.500000  7.500000
    small  5.500000  8.500000
foo large  2.000000  4.500000
    small  2.333333  4.333333
```

We can also calculate multiple types of aggregations for any given value column.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                        aggfunc={'D': np.mean,
...                                 'E': [min, max, np.mean]})
>>> table
                D    E
             mean  max      mean  min
A   C
bar large  5.500000  9.0  7.500000  6.0
    small  5.500000  9.0  8.500000  8.0
foo large  2.000000  5.0  4.500000  4.0
    small  2.333333  6.0  4.333333  2.0
```

pandas.DataFrame.plot

DataFrame.**plot**(**args*, ***kwargs*)

Make plots of Series or DataFrame.

Uses the backend specified by the option `plotting.backend`. By default, matplotlib is used.

Parameters

data [Series or DataFrame] The object for which the method is called.

x [label or position, default None] Only used if data is a DataFrame.

y [label, position or list of label, positions, default None] Allows plotting of one column versus another. Only used if data is a DataFrame.

kind [str] The kind of plot to produce:

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot.

ax [matplotlib axes object, default None] An axes of the current figure.

subplots [bool, default False] Make separate subplots for each column.

sharex [bool, default True if ax is None else False] In case `subplots=True`, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and `sharex=True` will alter all x axis labels for all axis in a figure.

sharey [bool, default False] In case `subplots=True`, share y axis and set some y axis labels to invisible.

layout [tuple, optional] (rows, columns) for the layout of subplots.

figsize [a tuple (width, height) in inches] Size of a figure object.

use_index [bool, default True] Use index as ticks for x axis.

title [str or list] Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and *subplots* is True, print each item in the list above the corresponding subplot.

grid [bool, default None (matlab style default)] Axis grid lines.

legend [bool or {'reverse'}] Place legend on axis subplots.

style [list or dict] The matplotlib line style per column.

logx [bool or 'sym', default False] Use log scaling or symlog scaling on x axis. .. versionchanged:: 0.25.0

logy [bool or 'sym' default False] Use log scaling or symlog scaling on y axis. .. versionchanged:: 0.25.0

loglog [bool or 'sym', default False] Use log scaling or symlog scaling on both x and y axes. .. versionchanged:: 0.25.0

xticks [sequence] Values to use for the xticks.

yticks [sequence] Values to use for the yticks.

xlim [2-tuple/list] Set the x limits of the current axes.

ylim [2-tuple/list] Set the y limits of the current axes.

xlabel [label, optional] Name to use for the xlabel on x-axis. Default uses index name as xlabel, or the x-column name for planar plots.

New in version 1.1.0.

Changed in version 1.2.0: Now applicable to planar plots (*scatter*, *hexbin*).

ylabel [label, optional] Name to use for the ylabel on y-axis. Default will show no ylabel, or the y-column name for planar plots.

New in version 1.1.0.

Changed in version 1.2.0: Now applicable to planar plots (*scatter*, *hexbin*).

rot [int, default None] Rotation for ticks (xticks for vertical, yticks for horizontal plots).

fontsize [int, default None] Font size for xticks and yticks.

colormap [str or matplotlib colormap object, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar [bool, optional] If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots).

position [float] Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center).

table [bool, Series or DataFrame, default False] If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr [DataFrame, Series, array-like, dict and str] See *Plotting with Error Bars* for detail.

xerr [DataFrame, Series, array-like, dict and str] Equivalent to yerr.

stacked [bool, default False in line and bar plots, and True in area plot] If True, create stacked plot.

sort_columns [bool, default False] Sort column names to determine plot ordering.

secondary_y [bool or sequence, default False] Whether to plot on the secondary y-axis if a list/tuple, which columns to plot on secondary y-axis.

mark_right [bool, default True] When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend.

include_bool [bool, default is False] If True, boolean values can be plotted.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

****kwargs** Options to pass to matplotlib plotting method.

Returns

matplotlib.axes.Axes or numpy.ndarray of them If the backend is not the default matplotlib one, the return value will be the object returned by the backend.

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

pandas.DataFrame.pop

DataFrame.**pop**(*item*)

Return item and drop from frame. Raise KeyError if not found.

Parameters

item [label] Label of column to be popped.

Returns

Series

Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                    ('parrot', 'bird', 24.0),
...                    ('lion', 'mammal', 80.5),
...                    ('monkey', 'mammal', np.nan)],
...                   columns=('name', 'class', 'max_speed'))
>>> df
     name   class  max_speed
0  falcon    bird      389.0
1  parrot    bird       24.0
2    lion  mammal       80.5
3  monkey  mammal        NaN
```

```
>>> df.pop('class')
0      bird
1      bird
2    mammal
3    mammal
Name: class, dtype: object
```

```
>>> df
     name  max_speed
0  falcon      389.0
1  parrot       24.0
2    lion       80.5
3  monkey        NaN
```

pandas.DataFrame.pow

DataFrame.**pow**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Exponential power of dataframe and other, element-wise (binary operator *pow*).

Equivalent to `dataframe ** other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rpow*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.prod

DataFrame.**prod**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, *min_count=0*, ***kwargs*)

Return the product of the values over the requested axis.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

By default, the product of an empty or all-NA Series is `1`

```
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

pandas.DataFrame.product

DataFrame.**product**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, *min_count=0*, ***kwargs*)

Return the product of the values over the requested axis.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

By default, the product of an empty or all-NA Series is `1`

```
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

pandas.DataFrame.quantile

`DataFrame.`**`quantile`**(*q=0.5*, *axis=0*, *numeric_only=True*, *interpolation='linear'*)

Return values at the given quantile over requested axis.

Parameters

q [float or array-like, default 0.5 (50% quantile)] Value between 0 <= q <= 1, the quantile(s) to compute.

axis [{0, 1, 'index', 'columns'}, default 0] Equals 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

numeric_only [bool, default True] If False, the quantile of datetime and timedelta data will be computed as well.

interpolation [{'linear', 'lower', 'higher', 'midpoint', 'nearest'}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points *i* and *j*:

- linear: *i* + *(j - i) * fraction*, where *fraction* is the fractional part of the index surrounded by *i* and *j*.
- lower: *i*.
- higher: *j*.
- nearest: *i* or *j* whichever is nearest.
- midpoint: (*i* + *j*) / 2.

Returns

Series or DataFrame

If `q` is an array, a DataFrame will be returned where the index is `q`, the columns are the columns of self, and the values are the quantiles.

If `q` is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

See also:

core.window.Rolling.quantile Rolling quantile.

numpy.percentile Numpy function to compute the percentile.

Examples

```
>>> df = pd.DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
...                   columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
Name: 0.1, dtype: float64
>>> df.quantile([.1, .5])
       a     b
0.1  1.3   3.7
0.5  2.5  55.0
```

Specifying *numeric_only=False* will also compute the quantile of datetime and timedelta data.

```
>>> df = pd.DataFrame({'A': [1, 2],
...                    'B': [pd.Timestamp('2010'),
...                          pd.Timestamp('2011')],
...                    'C': [pd.Timedelta('1 days'),
...                          pd.Timedelta('2 days')]})
>>> df.quantile(0.5, numeric_only=False)
A                    1.5
B    2010-07-02 12:00:00
C        1 days 12:00:00
Name: 0.5, dtype: object
```

pandas.DataFrame.query

DataFrame.**query**(*expr*, *inplace=False*, ***kwargs*)

Query the columns of a DataFrame with a boolean expression.

Parameters

expr [str] The query string to evaluate.

You can refer to variables in the environment by prefixing them with an '@' character like `@a + b`.

You can refer to column names that are not valid Python variable names by surrounding them in backticks. Thus, column names containing spaces or punctuations (besides underscores) or starting with digits must be surrounded by backticks. (For example, a column named "Area (cm^2) would be referenced as *Area (cm^2)*). Column names which are Python keywords (like "list", "for", "import", etc) cannot be used.

For example, if one of your columns is called `a a` and you want to sum it with `b`, your query should be `` `a a` + b ``.

New in version 0.25.0: Backtick quoting introduced.

New in version 1.0.0: Expanding functionality of backtick quoting for more than only spaces.

inplace [bool] Whether the query should modify the data in place or return a modified copy.

****kwargs** See the documentation for *eval()* for complete details on the keyword arguments accepted by *DataFrame.query()*.

Returns

DataFrame or None DataFrame resulting from the provided query expression or None if `inplace=True`.

See also:

eval Evaluate a string describing operations on DataFrame columns.

DataFrame.eval Evaluate a string describing operations on DataFrame columns.

Notes

The result of the evaluation of this expression is first passed to *DataFrame.loc* and if that fails because of a multidimensional key (e.g., a DataFrame) then the result will be passed to `DataFrame.__getitem__()`.

This method uses the top-level *eval()* function to evaluate the passed query.

The *query()* method uses a slightly modified Python syntax by default. For example, the `&` and `|` (bitwise) operators have the precedence of their boolean cousins, `and` and `or`. This *is* syntactically valid Python, however the semantics are different.

You can change the semantics of the expression by passing the keyword argument `parser='python'`. This enforces the same semantics as evaluation in Python space. Likewise, you can pass `engine='python'` to evaluate an expression using Python itself as a backend. This is not recommended as it is inefficient compared to using `numexpr` as the engine.

The *DataFrame.index* and *DataFrame.columns* attributes of the *DataFrame* instance are placed in the query namespace by default, which allows you to treat both the index and columns of the frame as a column in the frame. The identifier `index` is used for the frame index; you can also use the name of the index to identify it in a query. Please note that Python keywords may not be used as identifiers.

For further details and examples see the `query` documentation in *indexing*.

Backtick quoted variables

Backtick quoted variables are parsed as literal Python code and are converted internally to a Python valid identifier. This can lead to the following problems.

During parsing a number of disallowed characters inside the backtick quoted string are replaced by strings that are allowed as a Python identifier. These characters include all operators in Python, the space character, the question mark, the exclamation mark, the dollar sign, and the euro sign. For other characters that fall outside the ASCII range (U+0001..U+007F) and those that are not further specified in PEP 3131, the query parser will raise an error. This excludes whitespace different than the space character, but also the hashtag (as it is used for comments) and the backtick itself (backtick can also not be escaped).

In a special case, quotes that make a pair around a backtick can confuse the parser. For example, `` `it's` > `that's` `` will raise an error, as it forms a quoted string (`'s > `that'`) with a backtick inside.

See also the Python documentation about lexical analysis (https://docs.python.org/3/reference/lexical_analysis.html) in combination with the source code in `pandas.core.computation.parsing`.

Examples

```
>>> df = pd.DataFrame({'A': range(1, 6),
...                    'B': range(10, 0, -2),
...                    'C C': range(10, 5, -1)})
>>> df
   A   B  C C
0  1  10   10
1  2   8    9
2  3   6    8
3  4   4    7
4  5   2    6
>>> df.query('A > B')
   A  B  C C
4  5  2    6
```

The previous expression is equivalent to

```
>>> df[df.A > df.B]
   A  B  C C
4  5  2    6
```

For columns with spaces in their name, you can use backtick quoting.

```
>>> df.query('B == `C C`')
   A   B  C C
0  1  10   10
```

The previous expression is equivalent to

```
>>> df[df.B == df['C C']]
   A   B  C C
0  1  10   10
```

pandas.DataFrame.radd

DataFrame.**radd**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Addition of dataframe and other, element-wise (binary operator *radd*).

Equivalent to `other + dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *add*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.rank

DataFrame.**rank**(*axis=0*, *method='average'*, *numeric_only=None*, *na_option='keep'*, *ascending=True*, *pct=False*)

Compute numerical data ranks (1 through n) along axis.

By default, equal values are assigned a rank that is the average of the ranks of those values.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] Index to direct ranking.

method [{'average', 'min', 'max', 'first', 'dense'}, default 'average'] How to rank the group of records that have the same value (i.e. ties):

- average: average rank of the group
- min: lowest rank in the group
- max: highest rank in the group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups.

numeric_only [bool, optional] For DataFrame objects, rank only numeric columns if set to True.

na_option [{'keep', 'top', 'bottom'}, default 'keep'] How to rank NaN values:

- keep: assign NaN rank to NaN values
- top: assign smallest rank to NaN values if ascending
- bottom: assign highest rank to NaN values if ascending.

ascending [bool, default True] Whether or not the elements should be ranked in ascending order.

pct [bool, default False] Whether or not to display the returned rankings in percentile form.

Returns

same type as caller Return a Series or DataFrame with data ranks as values.

See also:

core.groupby.GroupBy.rank Rank of values within each group.

Examples

```
>>> df = pd.DataFrame(data={'Animal': ['cat', 'penguin', 'dog',
...                                    'spider', 'snake'],
...                         'Number_legs': [4, 2, 4, 8, np.nan]})
>>> df
    Animal  Number_legs
0      cat          4.0
1  penguin          2.0
2      dog          4.0
3   spider          8.0
4    snake          NaN
```

The following example shows how the method behaves with the above parameters:

- default_rank: this is the default behaviour obtained without using any parameter.
- max_rank: setting `method = 'max'` the records that have the same values are ranked using the highest rank (e.g.: since 'cat' and 'dog' are both in the 2nd and 3rd position, rank 3 is assigned.)
- NA_bottom: choosing `na_option = 'bottom'`, if there are records with NaN values they are placed at the bottom of the ranking.
- pct_rank: when setting `pct = True`, the ranking is expressed as percentile rank.

```
>>> df['default_rank'] = df['Number_legs'].rank()
>>> df['max_rank'] = df['Number_legs'].rank(method='max')
>>> df['NA_bottom'] = df['Number_legs'].rank(na_option='bottom')
>>> df['pct_rank'] = df['Number_legs'].rank(pct=True)
>>> df
    Animal  Number_legs  default_rank  max_rank  NA_bottom  pct_rank
0      cat          4.0           2.5       3.0        2.5     0.625
1  penguin          2.0           1.0       1.0        1.0     0.250
2      dog          4.0           2.5       3.0        2.5     0.625
3   spider          8.0           4.0       4.0        4.0     1.000
4    snake          NaN           NaN       NaN        5.0       NaN
```

pandas.DataFrame.rdiv

DataFrame.**rdiv**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Floating division of dataframe and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *truediv*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
```

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```
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.reindex

DataFrame.**reindex**(*labels=None*, *index=None*, *columns=None*, *axis=None*, *method=None*, *copy=True*, *level=None*, *fill_value=nan*, *limit=None*, *tolerance=None*)

Conform Series/DataFrame to new index with optional filling logic.

Places NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`.

Parameters

keywords for axes [array-like, optional] New labels / index to conform to, should be specified using keywords. Preferably an Index object to avoid duplicating data.

method [{None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don't fill gaps
- pad / ffill: Propagate last valid observation forward to next valid.
- backfill / bfill: Use next valid observation to fill gap.
- nearest: Use nearest valid observations to fill gap.

copy [bool, default True] Return a new object, even if the passed indexes are the same.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any "compatible" value.

limit [int, default None] Maximum number of consecutive elements to forward or backward fill.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

Returns

Series/DataFrame with changed index.

See also:

DataFrame.set_index Set row labels.

DataFrame.reset_index Remove row labels or move them to new columns.

DataFrame.reindex_like Change to same indices as other DataFrame.

Examples

`DataFrame.reindex` supports two calling conventions

- `(index=index_labels, columns=column_labels, ...)`
- `(labels, axis={'index', 'columns'}, ...)`

We *highly* recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({'http_status': [200, 200, 404, 404, 301],
...                    'response_time': [0.04, 0.02, 0.07, 0.08, 1.0]},
...                    index=index)
>>> df
           http_status  response_time
Firefox            200           0.04
Chrome             200           0.02
Safari             404           0.07
IE10               404           0.08
Konqueror          301           1.00
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned `NaN`.

```
>>> new_index = ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10',
...              'Chrome']
>>> df.reindex(new_index)
               http_status  response_time
Safari               404.0           0.07
Iceweasel              NaN            NaN
Comodo Dragon          NaN            NaN
IE10                 404.0           0.08
Chrome               200.0           0.02
```

We can fill in the missing values by passing a value to the keyword `fill_value`. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword `method` to fill the `NaN` values.

```
>>> df.reindex(new_index, fill_value=0)
               http_status  response_time
Safari                 404           0.07
Iceweasel                0           0.00
Comodo Dragon            0           0.00
IE10                   404           0.08
Chrome                 200           0.02
```

```
>>> df.reindex(new_index, fill_value='missing')
              http_status response_time
Safari                404          0.07
Iceweasel         missing       missing
Comodo Dragon     missing       missing
IE10                  404          0.08
Chrome                200          0.02
```

We can also reindex the columns.

```
>>> df.reindex(columns=['http_status', 'user_agent'])
           http_status  user_agent
Firefox            200         NaN
Chrome             200         NaN
Safari             404         NaN
IE10               404         NaN
Konqueror          301         NaN
```

Or we can use "axis-style" keyword arguments

```
>>> df.reindex(['http_status', 'user_agent'], axis="columns")
           http_status  user_agent
Firefox            200         NaN
Chrome             200         NaN
Safari             404         NaN
IE10               404         NaN
Konqueror          301         NaN
```

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame({"prices": [100, 101, np.nan, 100, 89, 88]},
...                    index=date_index)
>>> df2
            prices
2010-01-01   100.0
2010-01-02   101.0
2010-01-03     NaN
2010-01-04   100.0
2010-01-05    89.0
2010-01-06    88.0
```

Suppose we decide to expand the dataframe to cover a wider date range.

```
>>> date_index2 = pd.date_range('12/29/2009', periods=10, freq='D')
>>> df2.reindex(date_index2)
            prices
2009-12-29     NaN
2009-12-30     NaN
2009-12-31     NaN
2010-01-01   100.0
2010-01-02   101.0
2010-01-03     NaN
2010-01-04   100.0
2010-01-05    89.0
2010-01-06    88.0
2010-01-07     NaN
```

The index entries that did not have a value in the original data frame (for example, '2009-12-29') are by default filled with `NaN`. If desired, we can fill in the missing values using one of several options.

For example, to back-propagate the last valid value to fill the `NaN` values, pass `bfill` as an argument to the `method` keyword.

```
>>> df2.reindex(date_index2, method='bfill')
            prices
```

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```
2009-12-29   100.0
2009-12-30   100.0
2009-12-31   100.0
2010-01-01   100.0
2010-01-02   101.0
2010-01-03     NaN
2010-01-04   100.0
2010-01-05    89.0
2010-01-06    88.0
2010-01-07     NaN
```

Please note that the `NaN` value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the `NaN` values present in the original dataframe, use the `fillna()` method.

See the *user guide* for more.

pandas.DataFrame.reindex_like

`DataFrame.`**`reindex_like`**(*other*, *method=None*, *copy=True*, *limit=None*, *tolerance=None*)

Return an object with matching indices as other object.

Conform the object to the same index on all axes. Optional filling logic, placing NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False.

Parameters

other [Object of the same data type] Its row and column indices are used to define the new indices of this object.

method [{None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap.

copy [bool, default True] Return a new object, even if the passed indexes are the same.

limit [int, default None] Maximum number of consecutive labels to fill for inexact matches.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

Returns

Series or DataFrame Same type as caller, but with changed indices on each axis.

See also:

DataFrame.set_index Set row labels.

DataFrame.reset_index Remove row labels or move them to new columns.

DataFrame.reindex Change to new indices or expand indices.

Notes

Same as calling `.reindex(index=other.index, columns=other.columns,...)`.

Examples

```
>>> df1 = pd.DataFrame([[24.3, 75.7, 'high'],
...                     [31, 87.8, 'high'],
...                     [22, 71.6, 'medium'],
...                     [35, 95, 'medium']],
...                    columns=['temp_celsius', 'temp_fahrenheit',
...                             'windspeed'],
...                    index=pd.date_range(start='2014-02-12',
...                                        end='2014-02-15', freq='D'))
```

```
>>> df1
            temp_celsius  temp_fahrenheit windspeed
2014-02-12          24.3             75.7      high
2014-02-13          31.0             87.8      high
2014-02-14          22.0             71.6    medium
2014-02-15          35.0             95.0    medium
```

```
>>> df2 = pd.DataFrame([[28, 'low'],
...                     [30, 'low'],
...                     [35.1, 'medium']],
...                    columns=['temp_celsius', 'windspeed'],
...                    index=pd.DatetimeIndex(['2014-02-12', '2014-02-13',
...                                            '2014-02-15']))
```

```
>>> df2
            temp_celsius windspeed
2014-02-12          28.0       low
2014-02-13          30.0       low
2014-02-15          35.1    medium
```

```
>>> df2.reindex_like(df1)
            temp_celsius  temp_fahrenheit windspeed
2014-02-12          28.0              NaN       low
2014-02-13          30.0              NaN       low
2014-02-14           NaN              NaN       NaN
2014-02-15          35.1              NaN    medium
```

pandas.DataFrame.rename

DataFrame.**rename**(*mapper=None*, *index=None*, *columns=None*, *axis=None*, *copy=True*, *inplace=False*, *level=None*, *errors='ignore'*)

Alter axes labels.

Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is. Extra labels listed don't throw an error.

See the *user guide* for more.

Parameters

mapper [dict-like or function] Dict-like or function transformations to apply to that axis' values. Use either `mapper` and `axis` to specify the axis to target with `mapper`, or `index` and `columns`.

index [dict-like or function] Alternative to specifying axis (`mapper, axis=0` is equivalent to `index=mapper`).

columns [dict-like or function] Alternative to specifying axis (`mapper, axis=1` is equivalent to `columns=mapper`).

axis [{0 or 'index', 1 or 'columns'}, default 0] Axis to target with `mapper`. Can be either the axis name ('index', 'columns') or number (0, 1). The default is 'index'.

copy [bool, default True] Also copy underlying data.

inplace [bool, default False] Whether to return a new DataFrame. If True then value of copy is ignored.

level [int or level name, default None] In case of a MultiIndex, only rename labels in the specified level.

errors [{'ignore', 'raise'}, default 'ignore'] If 'raise', raise a *KeyError* when a dict-like *mapper*, *index*, or *columns* contains labels that are not present in the Index being transformed. If 'ignore', existing keys will be renamed and extra keys will be ignored.

Returns

DataFrame or None DataFrame with the renamed axis labels or None if `inplace=True`.

Raises

KeyError If any of the labels is not found in the selected axis and "errors='raise'".

See also:

DataFrame.rename_axis Set the name of the axis.

Examples

`DataFrame.rename` supports two calling conventions

- `(index=index_mapper, columns=columns_mapper, ...)`
- `(mapper, axis={'index', 'columns'}, ...)`

We *highly* recommend using keyword arguments to clarify your intent.

Rename columns using a mapping:

```
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
>>> df.rename(columns={"A": "a", "B": "c"})
   a  c
0  1  4
1  2  5
2  3  6
```

Rename index using a mapping:

```
>>> df.rename(index={0: "x", 1: "y", 2: "z"})
   A  B
x  1  4
y  2  5
z  3  6
```

Cast index labels to a different type:

```
>>> df.index
RangeIndex(start=0, stop=3, step=1)
>>> df.rename(index=str).index
Index(['0', '1', '2'], dtype='object')
```

```
>>> df.rename(columns={"A": "a", "B": "b", "C": "c"}, errors="raise")
Traceback (most recent call last):
KeyError: ['C'] not found in axis
```

Using axis-style parameters:

```
>>> df.rename(str.lower, axis='columns')
   a  b
0  1  4
1  2  5
2  3  6
```

```
>>> df.rename({1: 2, 2: 4}, axis='index')
   A  B
0  1  4
2  2  5
4  3  6
```

pandas.DataFrame.rename_axis

DataFrame.**rename_axis**(*mapper=None*, *index=None*, *columns=None*, *axis=None*, *copy=True*, *inplace=False*)

Set the name of the axis for the index or columns.

Parameters

mapper [scalar, list-like, optional] Value to set the axis name attribute.

index, columns [scalar, list-like, dict-like or function, optional] A scalar, list-like, dict-like or functions transformations to apply to that axis' values. Note that the `columns` parameter is not allowed if the object is a Series. This parameter only apply for DataFrame type objects.

Use either `mapper` and `axis` to specify the axis to target with `mapper`, or `index` and/or `columns`.

Changed in version 0.24.0.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to rename.

copy [bool, default True] Also copy underlying data.

inplace [bool, default False] Modifies the object directly, instead of creating a new Series or DataFrame.

Returns

Series, DataFrame, or None The same type as the caller or None if `inplace=True`.

See also:

Series.rename Alter Series index labels or name.

DataFrame.rename Alter DataFrame index labels or name.

Index.rename Set new names on index.

Notes

`DataFrame.rename_axis` supports two calling conventions

- `(index=index_mapper, columns=columns_mapper, ...)`
- `(mapper, axis={'index', 'columns'}, ...)`

The first calling convention will only modify the names of the index and/or the names of the Index object that is the columns. In this case, the parameter `copy` is ignored.

The second calling convention will modify the names of the corresponding index if mapper is a list or a scalar. However, if mapper is dict-like or a function, it will use the deprecated behavior of modifying the axis *labels*.

We *highly* recommend using keyword arguments to clarify your intent.

Examples

Series

```
>>> s = pd.Series(["dog", "cat", "monkey"])
>>> s
0       dog
1       cat
2    monkey
dtype: object
>>> s.rename_axis("animal")
animal
0    dog
1    cat
2    monkey
dtype: object
```

DataFrame

```
>>> df = pd.DataFrame({"num_legs": [4, 4, 2],
...                    "num_arms": [0, 0, 2]},
...                   ["dog", "cat", "monkey"])
>>> df
        num_legs  num_arms
dog             4         0
cat             4         0
monkey          2         2
>>> df = df.rename_axis("animal")
>>> df
        num_legs  num_arms
animal
dog             4         0
cat             4         0
monkey          2         2
>>> df = df.rename_axis("limbs", axis="columns")
>>> df
limbs   num_legs  num_arms
animal
dog             4         0
cat             4         0
monkey          2         2
```

MultiIndex

```
>>> df.index = pd.MultiIndex.from_product([['mammal'],
...                                        ['dog', 'cat', 'monkey']],
...                                       names=['type', 'name'])
>>> df
limbs          num_legs  num_arms
type   name
mammal dog             4         0
       cat             4         0
       monkey          2         2
```

```
>>> df.rename_axis(index={'type': 'class'})
limbs          num_legs  num_arms
class  name
```

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```
mammal dog            4         0
       cat            4         0
       monkey         2         2
```

```
>>> df.rename_axis(columns=str.upper)
LIMBS          num_legs  num_arms
type   name
mammal dog            4         0
       cat            4         0
       monkey         2         2
```

pandas.DataFrame.reorder_levels

DataFrame.**reorder_levels**(*order*, *axis=0*)

Rearrange index levels using input order. May not drop or duplicate levels.

Parameters

order [list of int or list of str] List representing new level order. Reference level by number (position) or by key (label).

axis [{0 or 'index', 1 or 'columns'}, default 0] Where to reorder levels.

Returns

DataFrame

pandas.DataFrame.replace

DataFrame.**replace**(*to_replace=None*, *value=None*, *inplace=False*, *limit=None*, *regex=False*, *method='pad'*)

Replace values given in *to_replace* with *value*.

Values of the DataFrame are replaced with other values dynamically. This differs from updating with `.loc` or `.iloc`, which require you to specify a location to update with some value.

Parameters

to_replace [str, regex, list, dict, Series, int, float, or None] How to find the values that will be replaced.

- numeric, str or regex:
  - numeric: numeric values equal to *to_replace* will be replaced with *value*
  - str: string exactly matching *to_replace* will be replaced with *value*
  - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to_replace* and *value* are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str, regex and numeric rules apply as above.

- dict:
  - Dicts can be used to specify different replacement values for different existing values. For example, `{'a': 'b', 'y': 'z'}` replaces the value 'a' with 'b' and 'y' with 'z'. To use a dict in this way the *value* parameter should be *None*.
  - For a DataFrame a dict can specify that different values should be replaced in different columns. For example, `{'a': 1, 'b': 'z'}` looks for the value 1 in column 'a' and the value 'z' in column 'b' and replaces these values with whatever is specified in *value*. The *value* parameter should not be `None` in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
  - For a DataFrame nested dictionaries, e.g., `{'a': {'b': np.nan}}`, are read as follows: look in column 'a' for the value 'b' and replace it with NaN. The *value* parameter should be `None` to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
- None:
  - This means that the *regex* argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also `None` then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value [scalar, dict, list, str, regex, default None] Value to replace any values matching *to_replace* with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace [bool, default False] If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit [int or None, default None] Maximum size gap to forward or backward fill.

regex [bool or same types as *to_replace*, default False] Whether to interpret *to_replace* and/or *value* as regular expressions. If this is `True` then *to_replace must* be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case *to_replace* must be `None`.

method [{'pad', 'ffill', 'bfill', *None*}] The method to use when for replacement, when *to_replace* is a scalar, list or tuple and *value* is `None`.

Returns

DataFrame or None Object after replacement or None if `inplace=True`.

Raises

AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is not a scalar, array-like, `dict`, or `None`
- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`

- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.
- When replacing multiple `bool` or `datetime64` objects and the arguments to *to_replace* does not match the type of the value being replaced

ValueError

- If a `list` or an `ndarray` is passed to *to_replace* and *value* but they are not the same length.

See also:

DataFrame.fillna Fill NA values.

DataFrame.where Replace values based on boolean condition.

Series.str.replace Simple string replacement.

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.
- When dict is used as the *to_replace* value, it is like key(s) in the dict are the to_replace part and value(s) in the dict are the value parameter.

Examples

Scalar `to_replace` and `value`

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0    5
1    1
2    2
3    3
4    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
...                    'B': [5, 6, 7, 8, 9],
...                    'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A  B  C
0  5  5  a
1  1  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

List-like `to_replace`

```
>>> df.replace([0, 1, 2, 3], 4)
   A  B  C
0  4  5  a
1  4  6  b
2  4  7  c
3  4  8  d
4  4  9  e
```

```
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A  B  C
0  4  5  a
1  3  6  b
2  2  7  c
3  1  8  d
4  4  9  e
```

```
>>> s.replace([1, 2], method='bfill')
0    0
1    3
2    3
3    3
4    4
dtype: int64
```

dict-like `to_replace`

```
>>> df.replace({0: 10, 1: 100})
     A  B  C
0   10  5  a
1  100  6  b
2    2  7  c
3    3  8  d
4    4  9  e
```

```
>>> df.replace({'A': 0, 'B': 5}, 100)
     A    B  C
0  100  100  a
1    1    6  b
2    2    7  c
3    3    8  d
4    4    9  e
```

```
>>> df.replace({'A': {0: 100, 4: 400}})
     A  B  C
0  100  5  a
1    1  6  b
2    2  7  c
3    3  8  d
4  400  9  e
```

Regular expression `to_replace`

```
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
...                    'B': ['abc', 'bar', 'xyz']})
```

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```
>>> df.replace(to_replace=r'^ba.$', value='new', regex=True)
      A    B
0   new  abc
1   foo  new
2  bait  xyz
```

```
>>> df.replace({'A': r'^ba.$'}, {'A': 'new'}, regex=True)
      A    B
0   new  abc
1   foo  bar
2  bait  xyz
```

```
>>> df.replace(regex=r'^ba.$', value='new')
      A    B
0   new  abc
1   foo  new
2  bait  xyz
```

```
>>> df.replace(regex={r'^ba.$': 'new', 'foo': 'xyz'})
      A    B
0   new  abc
1   xyz  new
2  bait  xyz
```

```
>>> df.replace(regex=[r'^ba.$', 'foo'], value='new')
      A    B
0   new  abc
1   new  new
2  bait  xyz
```

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the *to_replace* parameter:

```
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
```

When one uses a dict as the *to_replace* value, it is like the value(s) in the dict are equal to the *value* parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None)`:

```
>>> s.replace({'a': None})
0      10
1    None
2    None
3       b
4    None
dtype: object
```

When `value=None` and *to_replace* is a scalar, list or tuple, *replace* uses the method parameter (default 'pad') to do the replacement. So this is why the 'a' values are being replaced by 10 in rows 1 and 2 and 'b' in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad')`:

```
>>> s.replace('a', None)
0    10
```

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```
1    10
2    10
3     b
4     b
dtype: object
```

pandas.DataFrame.resample

DataFrame.**resample**(*rule*, *axis=0*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *base=None*, *on=None*, *level=None*, *origin='start_day'*, *offset=None*)

Resample time-series data.

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (*DatetimeIndex*, *PeriodIndex*, or *TimedeltaIndex*), or pass datetime-like values to the *on* or *level* keyword.

Parameters

rule [DateOffset, Timedelta or str] The offset string or object representing target conversion.

axis [{0 or 'index', 1 or 'columns'}, default 0] Which axis to use for up- or down-sampling. For *Series* this will default to 0, i.e. along the rows. Must be *DatetimeIndex*, *TimedeltaIndex* or *PeriodIndex*.

closed [{'right', 'left'}, default None] Which side of bin interval is closed. The default is 'left' for all frequency offsets except for 'M', 'A', 'Q', 'BM', 'BA', 'BQ', and 'W' which all have a default of 'right'.

label [{'right', 'left'}, default None] Which bin edge label to label bucket with. The default is 'left' for all frequency offsets except for 'M', 'A', 'Q', 'BM', 'BA', 'BQ', and 'W' which all have a default of 'right'.

convention [{'start', 'end', 's', 'e'}, default 'start'] For *PeriodIndex* only, controls whether to use the start or end of *rule*.

kind [{'timestamp', 'period'}, optional, default None] Pass 'timestamp' to convert the resulting index to a *DateTimeIndex* or 'period' to convert it to a *PeriodIndex*. By default the input representation is retained.

loffset [timedelta, default None] Adjust the resampled time labels.

Deprecated since version 1.1.0: You should add the loffset to the *df.index* after the resample. See below.

base [int, default 0] For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0.

Deprecated since version 1.1.0: The new arguments that you should use are 'offset' or 'origin'.

on [str, optional] For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.

level [str or int, optional] For a MultiIndex, level (name or number) to use for resampling. *level* must be datetime-like.

origin [{'epoch', 'start', 'start_day'}, Timestamp or str, default 'start_day'] The timestamp on which to adjust the grouping. The timezone of origin must match the timezone of the index. If a timestamp is not used, these values are also supported:

- 'epoch': *origin* is 1970-01-01
- 'start': *origin* is the first value of the timeseries
- 'start_day': *origin* is the first day at midnight of the timeseries

New in version 1.1.0.

offset [Timedelta or str, default is None] An offset timedelta added to the origin.

New in version 1.1.0.

Returns

Resampler object

See also:

groupby Group by mapping, function, label, or list of labels.

Series.resample Resample a Series.

DataFrame.resample Resample a DataFrame.

Notes

See the user guide for more.

To learn more about the offset strings, please see this link.

Examples

Start by creating a series with 9 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series
2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```
>>> series.resample('3T').sum()
2000-01-01 00:00:00     3
2000-01-01 00:03:00    12
2000-01-01 00:06:00    21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket `2000-01-01 00:03:00` contains the value 3, but the summed value in the resampled bucket with the label `2000-01-01 00:03:00` does not include 3 (if it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00     3
2000-01-01 00:06:00    12
2000-01-01 00:09:00    21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00     0
2000-01-01 00:03:00     6
2000-01-01 00:06:00    15
2000-01-01 00:09:00    15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.

```
>>> series.resample('30S').asfreq()[0:5]   # Select first 5 rows
2000-01-01 00:00:00   0.0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00   1.0
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00   2.0
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the `NaN` values using the `pad` method.

```
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    0
2000-01-01 00:01:00    1
2000-01-01 00:01:30    1
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the `NaN` values using the `bfill` method.

```
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    1
2000-01-01 00:01:00    1
2000-01-01 00:01:30    2
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Pass a custom function via `apply`

```
>>> def custom_resampler(array_like):
...     return np.sum(array_like) + 5
...
```

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```
>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00     8
2000-01-01 00:03:00    17
2000-01-01 00:06:00    26
Freq: 3T, dtype: int64
```

For a Series with a PeriodIndex, the keyword *convention* can be used to control whether to use the start or end of *rule*.

Resample a year by quarter using 'start' *convention*. Values are assigned to the first quarter of the period.

```
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01',
...                                             freq='A',
...                                             periods=2))
>>> s
2012    1
2013    2
Freq: A-DEC, dtype: int64
>>> s.resample('Q', convention='start').asfreq()
2012Q1    1.0
2012Q2    NaN
2012Q3    NaN
2012Q4    NaN
2013Q1    2.0
2013Q2    NaN
2013Q3    NaN
2013Q4    NaN
Freq: Q-DEC, dtype: float64
```

Resample quarters by month using 'end' *convention*. Values are assigned to the last month of the period.

```
>>> q = pd.Series([1, 2, 3, 4], index=pd.period_range('2018-01-01',
...                                                   freq='Q',
...                                                   periods=4))
>>> q
2018Q1    1
2018Q2    2
2018Q3    3
2018Q4    4
Freq: Q-DEC, dtype: int64
>>> q.resample('M', convention='end').asfreq()
2018-03    1.0
2018-04    NaN
2018-05    NaN
2018-06    2.0
2018-07    NaN
2018-08    NaN
2018-09    3.0
2018-10    NaN
2018-11    NaN
2018-12    4.0
Freq: M, dtype: float64
```

For DataFrame objects, the keyword *on* can be used to specify the column instead of the index for resampling.

```
>>> d = {'price': [10, 11, 9, 13, 14, 18, 17, 19],
...      'volume': [50, 60, 40, 100, 50, 100, 40, 50]}
>>> df = pd.DataFrame(d)
>>> df['week_starting'] = pd.date_range('01/01/2018',
...                                     periods=8,
...                                     freq='W')
>>> df
   price  volume week_starting
0     10      50    2018-01-07
1     11      60    2018-01-14
2      9      40    2018-01-21
3     13     100    2018-01-28
4     14      50    2018-02-04
5     18     100    2018-02-11
6     17      40    2018-02-18
7     19      50    2018-02-25
>>> df.resample('M', on='week_starting').mean()
               price  volume
week_starting
2018-01-31     10.75    62.5
2018-02-28     17.00    60.0
```

For a DataFrame with MultiIndex, the keyword *level* can be used to specify on which level the resampling needs to take place.

```
>>> days = pd.date_range('1/1/2000', periods=4, freq='D')
>>> d2 = {'price': [10, 11, 9, 13, 14, 18, 17, 19],
...       'volume': [50, 60, 40, 100, 50, 100, 40, 50]}
>>> df2 = pd.DataFrame(d2,
...                    index=pd.MultiIndex.from_product([days,
...                                                      ['morning',
...                                                       'afternoon']]
...                                                     ))
>>> df2
                     price  volume
2000-01-01 morning       10      50
           afternoon     11      60
2000-01-02 morning        9      40
           afternoon     13     100
2000-01-03 morning       14      50
           afternoon     18     100
2000-01-04 morning       17      40
           afternoon     19      50
>>> df2.resample('D', level=0).sum()
            price  volume
2000-01-01     21     110
2000-01-02     22     140
2000-01-03     32     150
2000-01-04     36      90
```

If you want to adjust the start of the bins based on a fixed timestamp:

```
>>> start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'
>>> rng = pd.date_range(start, end, freq='7min')
>>> ts = pd.Series(np.arange(len(rng)) * 3, index=rng)
>>> ts
2000-10-01 23:30:00     0
```

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```
2000-10-01 23:37:00     3
2000-10-01 23:44:00     6
2000-10-01 23:51:00     9
2000-10-01 23:58:00    12
2000-10-02 00:05:00    15
2000-10-02 00:12:00    18
2000-10-02 00:19:00    21
2000-10-02 00:26:00    24
Freq: 7T, dtype: int64
```

```
>>> ts.resample('17min').sum()
2000-10-01 23:14:00     0
2000-10-01 23:31:00     9
2000-10-01 23:48:00    21
2000-10-02 00:05:00    54
2000-10-02 00:22:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.resample('17min', origin='epoch').sum()
2000-10-01 23:18:00     0
2000-10-01 23:35:00    18
2000-10-01 23:52:00    27
2000-10-02 00:09:00    39
2000-10-02 00:26:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.resample('17min', origin='2000-01-01').sum()
2000-10-01 23:24:00     3
2000-10-01 23:41:00    15
2000-10-01 23:58:00    45
2000-10-02 00:15:00    45
Freq: 17T, dtype: int64
```

If you want to adjust the start of the bins with an *offset* Timedelta, the two following lines are equivalent:

```
>>> ts.resample('17min', origin='start').sum()
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.resample('17min', offset='23h30min').sum()
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

To replace the use of the deprecated *base* argument, you can now use *offset*, in this example it is equivalent to have *base=2*:

```
>>> ts.resample('17min', offset='2min').sum()
2000-10-01 23:16:00     0
2000-10-01 23:33:00     9
```

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```
2000-10-01 23:50:00    36
2000-10-02 00:07:00    39
2000-10-02 00:24:00    24
Freq: 17T, dtype: int64
```

To replace the use of the deprecated *loffset* argument:

```
>>> from pandas.tseries.frequencies import to_offset
>>> loffset = '19min'
>>> ts_out = ts.resample('17min').sum()
>>> ts_out.index = ts_out.index + to_offset(loffset)
>>> ts_out
2000-10-01 23:33:00     0
2000-10-01 23:50:00     9
2000-10-02 00:07:00    21
2000-10-02 00:24:00    54
2000-10-02 00:41:00    24
Freq: 17T, dtype: int64
```

pandas.DataFrame.reset_index

DataFrame.**reset_index**(*level=None*, *drop=False*, *inplace=False*, *col_level=0*, *col_fill=''*)

Reset the index, or a level of it.

Reset the index of the DataFrame, and use the default one instead. If the DataFrame has a MultiIndex, this method can remove one or more levels.

Parameters

level [int, str, tuple, or list, default None] Only remove the given levels from the index. Removes all levels by default.

drop [bool, default False] Do not try to insert index into dataframe columns. This resets the index to the default integer index.

inplace [bool, default False] Modify the DataFrame in place (do not create a new object).

col_level [int or str, default 0] If the columns have multiple levels, determines which level the labels are inserted into. By default it is inserted into the first level.

col_fill [object, default ''] If the columns have multiple levels, determines how the other levels are named. If None then the index name is repeated.

Returns

DataFrame or None DataFrame with the new index or None if `inplace=True`.

See also:

DataFrame.set_index Opposite of reset_index.

DataFrame.reindex Change to new indices or expand indices.

DataFrame.reindex_like Change to same indices as other DataFrame.

Examples

```
>>> df = pd.DataFrame([('bird', 389.0),
...                    ('bird', 24.0),
...                    ('mammal', 80.5),
...                    ('mammal', np.nan)],
...                   index=['falcon', 'parrot', 'lion', 'monkey'],
...                   columns=('class', 'max_speed'))
>>> df
         class  max_speed
falcon    bird      389.0
parrot    bird       24.0
lion    mammal       80.5
monkey  mammal        NaN
```

When we reset the index, the old index is added as a column, and a new sequential index is used:

```
>>> df.reset_index()
    index   class  max_speed
0  falcon    bird      389.0
1  parrot    bird       24.0
2    lion  mammal       80.5
3  monkey  mammal        NaN
```

We can use the *drop* parameter to avoid the old index being added as a column:

```
>>> df.reset_index(drop=True)
    class  max_speed
0    bird      389.0
1    bird       24.0
2  mammal       80.5
3  mammal        NaN
```

You can also use *reset_index* with *MultiIndex*.

```
>>> index = pd.MultiIndex.from_tuples([('bird', 'falcon'),
...                                    ('bird', 'parrot'),
...                                    ('mammal', 'lion'),
...                                    ('mammal', 'monkey')],
...                                   names=['class', 'name'])
>>> columns = pd.MultiIndex.from_tuples([('speed', 'max'),
...                                      ('species', 'type')])
>>> df = pd.DataFrame([(389.0, 'fly'),
...                    ( 24.0, 'fly'),
...                    ( 80.5, 'run'),
...                    (np.nan, 'jump')],
...                   index=index,
...                   columns=columns)
>>> df
               speed species
                 max    type
class  name
bird   falcon  389.0     fly
       parrot   24.0     fly
mammal lion     80.5     run
       monkey    NaN    jump
```

If the index has multiple levels, we can reset a subset of them:

```
>>> df.reset_index(level='class')
         class  speed species
                  max    type
name
falcon    bird  389.0     fly
parrot    bird   24.0     fly
lion    mammal   80.5     run
monkey  mammal    NaN    jump
```

If we are not dropping the index, by default, it is placed in the top level. We can place it in another level:

```
>>> df.reset_index(level='class', col_level=1)
                speed species
         class    max    type
name
falcon    bird  389.0     fly
parrot    bird   24.0     fly
lion    mammal   80.5     run
monkey  mammal    NaN    jump
```

When the index is inserted under another level, we can specify under which one with the parameter *col_fill*:

```
>>> df.reset_index(level='class', col_level=1, col_fill='species')
              species  speed species
                class    max    type
name
falcon           bird  389.0     fly
parrot           bird   24.0     fly
lion           mammal   80.5     run
monkey         mammal    NaN    jump
```

If we specify a nonexistent level for *col_fill*, it is created:

```
>>> df.reset_index(level='class', col_level=1, col_fill='genus')
                genus  speed species
                class    max    type
name
falcon           bird  389.0     fly
parrot           bird   24.0     fly
lion           mammal   80.5     run
monkey         mammal    NaN    jump
```

pandas.DataFrame.rfloordiv

`DataFrame.`**`rfloordiv`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Integer division of dataframe and other, element-wise (binary operator *rfloordiv*).

Equivalent to `other // dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *floordiv*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.rmod

DataFrame.**rmod**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Modulo of dataframe and other, element-wise (binary operator *rmod*).

Equivalent to `other % dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *mod*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
```

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```
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.rmul

DataFrame.**rmul**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Multiplication of dataframe and other, element-wise (binary operator *rmul*).

Equivalent to `other * dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *mul*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
```

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```
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.rolling

DataFrame.**rolling**(*window*, *min_periods=None*, *center=False*, *win_type=None*, *on=None*, *axis=0*, *closed=None*)

Provide rolling window calculations.

Parameters

window [int, offset, or BaseIndexer subclass] Size of the moving window. This is the number of observations used for calculating the statistic. Each window will be a fixed size.

If its an offset then this will be the time period of each window. Each window will be a variable sized based on the observations included in the time-period. This is only valid for datetimelike indexes.

If a BaseIndexer subclass is passed, calculates the window boundaries based on the defined `get_window_bounds` method. Additional rolling keyword arguments, namely *min_periods*, *center*, and *closed* will be passed to *get_window_bounds*.

min_periods [int, default None] Minimum number of observations in window required to have a value (otherwise result is NA). For a window that is specified by an offset, *min_periods* will default to 1. Otherwise, *min_periods* will default to the size of the window.

center [bool, default False] Set the labels at the center of the window.

win_type [str, default None] Provide a window type. If `None`, all points are evenly weighted. See the notes below for further information.

on [str, optional] For a DataFrame, a datetime-like column or MultiIndex level on which to calculate the rolling window, rather than the DataFrame's index. Provided integer column is ignored and excluded from result since an integer index is not used to calculate the rolling window.

axis [int or str, default 0]

closed [str, default None] Make the interval closed on the 'right', 'left', 'both' or 'neither' endpoints. Defaults to 'right'.

Changed in version 1.2.0: The closed parameter with fixed windows is now supported.

Returns

a Window or Rolling sub-classed for the particular operation

See also:

expanding Provides expanding transformations.

ewm Provides exponential weighted functions.

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

To learn more about the offsets & frequency strings, please see this link.

If `win_type=None`, all points are evenly weighted; otherwise, `win_type` can accept a string of any scipy.signal window function.

Certain Scipy window types require additional parameters to be passed in the aggregation function. The additional parameters must match the keywords specified in the Scipy window type method signature. Please see the third example below on how to add the additional parameters.

Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

Rolling sum with a window length of 2, using the 'triang' window type.

```
>>> df.rolling(2, win_type='triang').sum()
     B
0  NaN
1  0.5
2  1.5
3  NaN
4  NaN
```

Rolling sum with a window length of 2, using the 'gaussian' window type (note how we need to specify std).

```
>>> df.rolling(2, win_type='gaussian').sum(std=3)
          B
0       NaN
1  0.986207
2  2.958621
3       NaN
4       NaN
```

Rolling sum with a window length of 2, min_periods defaults to the window length.

```
>>> df.rolling(2).sum()
     B
0  NaN
1  1.0
2  3.0
3  NaN
4  NaN
```

Same as above, but explicitly set the min_periods

```
>>> df.rolling(2, min_periods=1).sum()
     B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0
```

Same as above, but with forward-looking windows

```
>>> indexer = pd.api.indexers.FixedForwardWindowIndexer(window_size=2)
>>> df.rolling(window=indexer, min_periods=1).sum()
     B
0  1.0
1  3.0
2  2.0
3  4.0
4  4.0
```

A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
...                   index = [pd.Timestamp('20130101 09:00:00'),
...                            pd.Timestamp('20130101 09:00:02'),
...                            pd.Timestamp('20130101 09:00:03'),
...                            pd.Timestamp('20130101 09:00:05'),
...                            pd.Timestamp('20130101 09:00:06')])
```

```
>>> df
                       B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min_periods is 1.

```
>>> df.rolling('2s').sum()
                       B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

pandas.DataFrame.round

DataFrame.**round**(*decimals=0*, **args*, ***kwargs*)

Round a DataFrame to a variable number of decimal places.

Parameters

decimals [int, dict, Series] Number of decimal places to round each column to. If an int is given, round each column to the same number of places. Otherwise dict and Series round to variable numbers of places. Column names should be in the keys if *decimals* is a dict-like, or in the index if *decimals* is a Series. Any columns not included in *decimals* will be left as is. Elements of *decimals* which are not columns of the input will be ignored.

***args** Additional keywords have no effect but might be accepted for compatibility with numpy.

****kwargs** Additional keywords have no effect but might be accepted for compatibility with numpy.

Returns

DataFrame A DataFrame with the affected columns rounded to the specified number of decimal places.

See also:

numpy.around Round a numpy array to the given number of decimals.

Series.round Round a Series to the given number of decimals.

Examples

```
>>> df = pd.DataFrame([(.21, .32), (.01, .67), (.66, .03), (.21, .18)],
...                   columns=['dogs', 'cats'])
>>> df
    dogs  cats
0   0.21  0.32
1   0.01  0.67
2   0.66  0.03
3   0.21  0.18
```

By providing an integer each column is rounded to the same number of decimal places

```
>>> df.round(1)
    dogs  cats
0   0.2   0.3
1   0.0   0.7
2   0.7   0.0
3   0.2   0.2
```

With a dict, the number of places for specific columns can be specified with the column names as key and the number of decimal places as value

```
>>> df.round({'dogs': 1, 'cats': 0})
    dogs  cats
0   0.2   0.0
1   0.0   1.0
```

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```
2   0.7   0.0
3   0.2   0.0
```

Using a Series, the number of places for specific columns can be specified with the column names as index and the number of decimal places as value

```
>>> decimals = pd.Series([0, 1], index=['cats', 'dogs'])
>>> df.round(decimals)
    dogs  cats
0   0.2   0.0
1   0.0   1.0
2   0.7   0.0
3   0.2   0.0
```

pandas.DataFrame.rpow

DataFrame.**rpow**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Exponential power of dataframe and other, element-wise (binary operator *rpow*).

Equivalent to `other ** dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *pow*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.rsub

DataFrame.**rsub**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Subtraction of dataframe and other, element-wise (binary operator *rsub*).

Equivalent to `other - dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *sub*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
```

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```
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.rtruediv

DataFrame.**rtruediv**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Floating division of dataframe and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *truediv*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
```

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```
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.sample

DataFrame.**sample**(*n=None*, *frac=None*, *replace=False*, *weights=None*, *random_state=None*, *axis=None*)

Return a random sample of items from an axis of object.

You can use *random_state* for reproducibility.

Parameters

n [int, optional] Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac [float, optional] Fraction of axis items to return. Cannot be used with *n*.

replace [bool, default False] Allow or disallow sampling of the same row more than once.

weights [str or ndarray-like, optional] Default 'None' results in equal probability weighting. If passed a Series, will align with target object on index. Index values in weights not found in sampled object will be ignored and index values in sampled object not in weights will be assigned weights of zero. If called on a DataFrame, will accept the name of a column when axis = 0. Unless weights are a Series, weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. Infinite values not allowed.

random_state [int, array-like, BitGenerator, np.random.RandomState, optional] If int, array-like, or BitGenerator (NumPy>=1.17), seed for random number generator If np.random.RandomState, use as numpy RandomState object.

Changed in version 1.1.0: array-like and BitGenerator (for NumPy>=1.17) object now passed to np.random.RandomState() as seed

axis [{0 or 'index', 1 or 'columns', None}, default None] Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames).

Returns

Series or DataFrame A new object of same type as caller containing *n* items randomly sampled from the caller object.

See also:

DataFrameGroupBy.sample Generates random samples from each group of a DataFrame object.

SeriesGroupBy.sample Generates random samples from each group of a Series object.

numpy.random.choice Generates a random sample from a given 1-D numpy array.

Notes

If *frac* > 1, *replacement* should be set to *True*.

Examples

```
>>> df = pd.DataFrame({'num_legs': [2, 4, 8, 0],
...                    'num_wings': [2, 0, 0, 0],
...                    'num_specimen_seen': [10, 2, 1, 8]},
...                   index=['falcon', 'dog', 'spider', 'fish'])
>>> df
        num_legs  num_wings  num_specimen_seen
falcon         2          2                 10
dog            4          0                  2
spider         8          0                  1
fish           0          0                  8
```

Extract 3 random elements from the `Series` `df['num_legs']`: Note that we use *random_state* to ensure the reproducibility of the examples.

```
>>> df['num_legs'].sample(n=3, random_state=1)
fish      0
spider    8
falcon    2
Name: num_legs, dtype: int64
```

A random 50% sample of the `DataFrame` with replacement:

```
>>> df.sample(frac=0.5, replace=True, random_state=1)
      num_legs  num_wings  num_specimen_seen
dog          4          0                  2
fish         0          0                  8
```

An upsample sample of the `DataFrame` with replacement: Note that *replace* parameter has to be *True* for *frac* parameter > 1.

```
>>> df.sample(frac=2, replace=True, random_state=1)
        num_legs  num_wings  num_specimen_seen
dog            4          0                  2
fish           0          0                  8
falcon         2          2                 10
falcon         2          2                 10
fish           0          0                  8
dog            4          0                  2
fish           0          0                  8
dog            4          0                  2
```

Using a DataFrame column as weights. Rows with larger value in the *num_specimen_seen* column are more likely to be sampled.

```
>>> df.sample(n=2, weights='num_specimen_seen', random_state=1)
        num_legs  num_wings  num_specimen_seen
falcon         2          2                 10
fish           0          0                  8
```

pandas.DataFrame.select_dtypes

DataFrame.**select_dtypes**(*include=None*, *exclude=None*)

Return a subset of the DataFrame's columns based on the column dtypes.

Parameters

include, exclude [scalar or list-like] A selection of dtypes or strings to be included/excluded. At least one of these parameters must be supplied.

Returns

DataFrame The subset of the frame including the dtypes in `include` and excluding the dtypes in `exclude`.

Raises

ValueError

- If both of `include` and `exclude` are empty
- If `include` and `exclude` have overlapping elements
- If any kind of string dtype is passed in.

See also:

DataFrame.dtypes Return Series with the data type of each column.

Notes

- To select all *numeric* types, use `np.number` or `'number'`
- To select strings you must use the `object` dtype, but note that this will return *all* object dtype columns
- See the numpy dtype hierarchy
- To select datetimes, use `np.datetime64`, `'datetime'` or `'datetime64'`
- To select timedeltas, use `np.timedelta64`, `'timedelta'` or `'timedelta64'`
- To select Pandas categorical dtypes, use `'category'`
- To select Pandas datetimetz dtypes, use `'datetimetz'` (new in 0.20.0) or `'datetime64[ns, tz]'`

Examples

```
>>> df = pd.DataFrame({'a': [1, 2] * 3,
...                    'b': [True, False] * 3,
...                    'c': [1.0, 2.0] * 3})
>>> df
        a      b  c
0       1   True  1.0
1       2  False  2.0
2       1   True  1.0
3       2  False  2.0
4       1   True  1.0
5       2  False  2.0
```

```
>>> df.select_dtypes(include='bool')
   b
0  True
1  False
2  True
3  False
4  True
5  False
```

```
>>> df.select_dtypes(include=['float64'])
   c
0  1.0
1  2.0
2  1.0
3  2.0
4  1.0
5  2.0
```

```
>>> df.select_dtypes(exclude=['int64'])
       b    c
0   True  1.0
1  False  2.0
2   True  1.0
3  False  2.0
4   True  1.0
5  False  2.0
```

pandas.DataFrame.sem

DataFrame.**sem**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis [{index (0), columns (1)}]

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

Series or DataFrame (if level specified)

Notes

To have the same behaviour as *numpy.std*, use *ddof=0* (instead of the default *ddof=1*)

pandas.DataFrame.set_axis

DataFrame.**set_axis**(*labels*, *axis=0*, *inplace=False*)

Assign desired index to given axis.

Indexes for column or row labels can be changed by assigning a list-like or Index.

Parameters

labels [list-like, Index] The values for the new index.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to update. The value 0 identifies the rows, and 1 identifies the columns.

inplace [bool, default False] Whether to return a new DataFrame instance.

Returns

renamed [DataFrame or None] An object of type DataFrame or None if `inplace=True`.

See also:

DataFrame.rename_axis Alter the name of the index or columns.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
```

Change the row labels.

```
>>> df.set_axis(['a', 'b', 'c'], axis='index')
   A  B
a  1  4
b  2  5
c  3  6
```

Change the column labels.

```
>>> df.set_axis(['I', 'II'], axis='columns')
   I  II
0  1   4
1  2   5
2  3   6
```

Now, update the labels inplace.

```
>>> df.set_axis(['i', 'ii'], axis='columns', inplace=True)
>>> df
   i  ii
0  1   4
1  2   5
2  3   6
```

pandas.DataFrame.set_flags

DataFrame.**set_flags**(*, *copy=False*, *allows_duplicate_labels=None*)

Return a new object with updated flags.

Parameters

allows_duplicate_labels [bool, optional] Whether the returned object allows duplicate labels.

Returns

Series or DataFrame The same type as the caller.

See also:

DataFrame.attrs Global metadata applying to this dataset.

DataFrame.flags Global flags applying to this object.

Notes

This method returns a new object that's a view on the same data as the input. Mutating the input or the output values will be reflected in the other.

This method is intended to be used in method chains.

"Flags" differ from "metadata". Flags reflect properties of the pandas object (the Series or DataFrame). Metadata refer to properties of the dataset, and should be stored in *DataFrame.attrs*.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2]})
>>> df.flags.allows_duplicate_labels
True
>>> df2 = df.set_flags(allows_duplicate_labels=False)
>>> df2.flags.allows_duplicate_labels
False
```

pandas.DataFrame.set_index

DataFrame.**set_index**(*keys*, *drop=True*, *append=False*, *inplace=False*, *verify_integrity=False*)

Set the DataFrame index using existing columns.

Set the DataFrame index (row labels) using one or more existing columns or arrays (of the correct length). The index can replace the existing index or expand on it.

Parameters

keys [label or array-like or list of labels/arrays] This parameter can be either a single column key, a single array of the same length as the calling DataFrame, or a list containing an arbitrary combination of column keys and arrays. Here, "array" encompasses *Series*, *Index*, np.ndarray, and instances of Iterator.

drop [bool, default True] Delete columns to be used as the new index.

append [bool, default False] Whether to append columns to existing index.

inplace [bool, default False] If True, modifies the DataFrame in place (do not create a new object).

verify_integrity [bool, default False] Check the new index for duplicates. Otherwise defer the check until necessary. Setting to False will improve the performance of this method.

Returns

DataFrame or None Changed row labels or None if `inplace=True`.

See also:

DataFrame.reset_index Opposite of set_index.

DataFrame.reindex Change to new indices or expand indices.

DataFrame.reindex_like Change to same indices as other DataFrame.

Examples

```
>>> df = pd.DataFrame({'month': [1, 4, 7, 10],
...                    'year': [2012, 2014, 2013, 2014],
...                    'sale': [55, 40, 84, 31]})
>>> df
   month  year  sale
0      1  2012    55
1      4  2014    40
2      7  2013    84
3     10  2014    31
```

Set the index to become the 'month' column:

```
>>> df.set_index('month')
       year  sale
month
1      2012    55
4      2014    40
7      2013    84
10     2014    31
```

Create a MultiIndex using columns 'year' and 'month':

```
>>> df.set_index(['year', 'month'])
            sale
year  month
2012  1     55
2014  4     40
2013  7     84
2014  10    31
```

Create a MultiIndex using an Index and a column:

```
>>> df.set_index([pd.Index([1, 2, 3, 4]), 'year'])
         month  sale
   year
1  2012  1      55
2  2014  4      40
```

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```
3  2013  7      84
4  2014  10     31
```

Create a MultiIndex using two Series:

```
>>> s = pd.Series([1, 2, 3, 4])
>>> df.set_index([s, s**2])
      month  year  sale
1 1       1  2012    55
2 4       4  2014    40
3 9       7  2013    84
4 16     10  2014    31
```

pandas.DataFrame.shift

DataFrame.**shift**(*periods=1*, *freq=None*, *axis=0*, *fill_value=<object object>*)

Shift index by desired number of periods with an optional time *freq*.

When *freq* is not passed, shift the index without realigning the data. If *freq* is passed (in this case, the index must be date or datetime, or it will raise a *NotImplementedError*), the index will be increased using the periods and the *freq*. *freq* can be inferred when specified as "infer" as long as either freq or inferred_freq attribute is set in the index.

Parameters

periods [int] Number of periods to shift. Can be positive or negative.

freq [DateOffset, tseries.offsets, timedelta, or str, optional] Offset to use from the tseries module or time rule (e.g. 'EOM'). If *freq* is specified then the index values are shifted but the data is not realigned. That is, use *freq* if you would like to extend the index when shifting and preserve the original data. If *freq* is specified as "infer" then it will be inferred from the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown.

axis [{0 or 'index', 1 or 'columns', None}, default None] Shift direction.

fill_value [object, optional] The scalar value to use for newly introduced missing values. the default depends on the dtype of *self*. For numeric data, `np.nan` is used. For datetime, timedelta, or period data, etc. `NaT` is used. For extension dtypes, `self.dtype.na_value` is used.

Changed in version 1.1.0.

Returns

DataFrame Copy of input object, shifted.

See also:

Index.shift Shift values of Index.

DatetimeIndex.shift Shift values of DatetimeIndex.

PeriodIndex.shift Shift values of PeriodIndex.

tshift Shift the time index, using the index's frequency if available.

Examples

```
>>> df = pd.DataFrame({"Col1": [10, 20, 15, 30, 45],
...                    "Col2": [13, 23, 18, 33, 48],
...                    "Col3": [17, 27, 22, 37, 52]},
...                   index=pd.date_range("2020-01-01", "2020-01-05"))
>>> df
            Col1  Col2  Col3
2020-01-01    10    13    17
2020-01-02    20    23    27
2020-01-03    15    18    22
2020-01-04    30    33    37
2020-01-05    45    48    52
```

```
>>> df.shift(periods=3)
            Col1  Col2  Col3
2020-01-01   NaN   NaN   NaN
2020-01-02   NaN   NaN   NaN
2020-01-03   NaN   NaN   NaN
2020-01-04  10.0  13.0  17.0
2020-01-05  20.0  23.0  27.0
```

```
>>> df.shift(periods=1, axis="columns")
            Col1  Col2  Col3
2020-01-01   NaN    10    13
2020-01-02   NaN    20    23
2020-01-03   NaN    15    18
2020-01-04   NaN    30    33
2020-01-05   NaN    45    48
```

```
>>> df.shift(periods=3, fill_value=0)
            Col1  Col2  Col3
2020-01-01     0     0     0
2020-01-02     0     0     0
2020-01-03     0     0     0
2020-01-04    10    13    17
2020-01-05    20    23    27
```

```
>>> df.shift(periods=3, freq="D")
            Col1  Col2  Col3
2020-01-04    10    13    17
2020-01-05    20    23    27
2020-01-06    15    18    22
2020-01-07    30    33    37
2020-01-08    45    48    52
```

```
>>> df.shift(periods=3, freq="infer")
            Col1  Col2  Col3
2020-01-04    10    13    17
2020-01-05    20    23    27
2020-01-06    15    18    22
2020-01-07    30    33    37
2020-01-08    45    48    52
```

pandas.DataFrame.skew

DataFrame.**skew**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return unbiased skew over requested axis.

Normalized by N-1.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.slice_shift

DataFrame.**slice_shift**(*periods=1*, *axis=0*)

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Deprecated since version 1.2.0: slice_shift is deprecated, use DataFrame/Series.shift instead.

Parameters

periods [int] Number of periods to move, can be positive or negative.

Returns

shifted [same type as caller]

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.DataFrame.sort_index

DataFrame.**sort_index**(*axis=0*, *level=None*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*, *sort_remaining=True*, *ignore_index=False*, *key=None*)

Sort object by labels (along an axis).

Returns a new DataFrame sorted by label if *inplace* argument is `False`, otherwise updates the original DataFrame and returns None.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis along which to sort. The value 0 identifies the rows, and 1 identifies the columns.

level [int or level name or list of ints or list of level names] If not None, sort on values in specified index level(s).

ascending [bool or list of bools, default True] Sort ascending vs. descending. When the index is a MultiIndex the sort direction can be controlled for each level individually.

inplace [bool, default False] If True, perform operation in-place.

kind [{'quicksort', 'mergesort', 'heapsort'}, default 'quicksort'] Choice of sorting algorithm. See also ndarray.np.sort for more information. *mergesort* is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

na_position [{'first', 'last'}, default 'last'] Puts NaNs at the beginning if *first*; *last* puts NaNs at the end. Not implemented for MultiIndex.

sort_remaining [bool, default True] If True and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level.

ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, …, n - 1.

New in version 1.0.0.

key [callable, optional] If not None, apply the key function to the index values before sorting. This is similar to the *key* argument in the builtin `sorted()` function, with the notable difference that this *key* function should be *vectorized*. It should expect an `Index` and return an `Index` of the same shape. For MultiIndex inputs, the key is applied *per level*.

New in version 1.1.0.

Returns

DataFrame or None The original DataFrame sorted by the labels or None if `inplace=True`.

See also:

Series.sort_index Sort Series by the index.

DataFrame.sort_values Sort DataFrame by the value.

Series.sort_values Sort Series by the value.

Examples

```
>>> df = pd.DataFrame([1, 2, 3, 4, 5], index=[100, 29, 234, 1, 150],
...                   columns=['A'])
>>> df.sort_index()
     A
1    4
29   2
100  1
150  5
234  3
```

By default, it sorts in ascending order, to sort in descending order, use `ascending=False`

```
>>> df.sort_index(ascending=False)
     A
234  3
150  5
100  1
29   2
1    4
```

A key function can be specified which is applied to the index before sorting. For a `MultiIndex` this is applied to each level separately.

```
>>> df = pd.DataFrame({"a": [1, 2, 3, 4]}, index=['A', 'b', 'C', 'd'])
>>> df.sort_index(key=lambda x: x.str.lower())
   a
A  1
b  2
C  3
d  4
```

pandas.DataFrame.sort_values

`DataFrame.`**`sort_values`**(*by*, *axis=0*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*, *ignore_index=False*, *key=None*)

Sort by the values along either axis.

Parameters

by [str or list of str] Name or list of names to sort by.

- if *axis* is 0 or *'index'* then *by* may contain index levels and/or column labels.
- if *axis* is 1 or *'columns'* then *by* may contain column levels and/or index labels.

axis [{0 or 'index', 1 or 'columns'}, default 0] Axis to be sorted.

ascending [bool or list of bool, default True] Sort ascending vs. descending. Specify list for multiple sort orders. If this is a list of bools, must match the length of the by.

inplace [bool, default False] If True, perform operation in-place.

kind [{'quicksort', 'mergesort', 'heapsort'}, default 'quicksort'] Choice of sorting algorithm. See also ndarray.np.sort for more information. *mergesort* is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

na_position [{'first', 'last'}, default 'last'] Puts NaNs at the beginning if *first*; *last* puts NaNs at the end.

ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, . . . , n - 1.

New in version 1.0.0.

key [callable, optional] Apply the key function to the values before sorting. This is similar to the *key* argument in the builtin `sorted()` function, with the notable difference that this *key* function should be *vectorized*. It should expect a `Series` and return a Series with the same shape as the input. It will be applied to each column in *by* independently.

New in version 1.1.0.

Returns

DataFrame or None DataFrame with sorted values or None if `inplace=True`.

See also:

DataFrame.sort_index Sort a DataFrame by the index.

Series.sort_values Similar method for a Series.

Examples

```
>>> df = pd.DataFrame({
...     'col1': ['A', 'A', 'B', np.nan, 'D', 'C'],
...     'col2': [2, 1, 9, 8, 7, 4],
...     'col3': [0, 1, 9, 4, 2, 3],
...     'col4': ['a', 'B', 'c', 'D', 'e', 'F']
... })
>>> df
  col1  col2  col3 col4
0    A     2     0    a
1    A     1     1    B
2    B     9     9    c
3  NaN     8     4    D
4    D     7     2    e
5    C     4     3    F
```

Sort by col1

```
>>> df.sort_values(by=['col1'])
  col1  col2  col3 col4
0    A     2     0    a
1    A     1     1    B
2    B     9     9    c
5    C     4     3    F
4    D     7     2    e
3  NaN     8     4    D
```

Sort by multiple columns

```
>>> df.sort_values(by=['col1', 'col2'])
  col1  col2  col3 col4
1    A     1     1    B
0    A     2     0    a
2    B     9     9    c
5    C     4     3    F
4    D     7     2    e
3  NaN     8     4    D
```

Sort Descending

```
>>> df.sort_values(by='col1', ascending=False)
  col1  col2  col3 col4
4    D     7     2    e
5    C     4     3    F
2    B     9     9    c
```

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```
0    A      2      0    a
1    A      1      1    B
3  NaN      8      4    D
```

Putting NAs first

```
>>> df.sort_values(by='col1', ascending=False, na_position='first')
  col1  col2  col3 col4
3  NaN     8     4    D
4    D     7     2    e
5    C     4     3    F
2    B     9     9    c
0    A     2     0    a
1    A     1     1    B
```

Sorting with a key function

```
>>> df.sort_values(by='col4', key=lambda col: col.str.lower())
   col1  col2  col3 col4
0    A     2     0    a
1    A     1     1    B
2    B     9     9    c
3  NaN     8     4    D
4    D     7     2    e
5    C     4     3    F
```

Natural sort with the key argument, using the *natsort <https://github.com/SethMMorton/natsort>* package.

```
>>> df = pd.DataFrame({
...    "time": ['0hr', '128hr', '72hr', '48hr', '96hr'],
...    "value": [10, 20, 30, 40, 50]
... })
>>> df
    time  value
0    0hr     10
1  128hr     20
2   72hr     30
3   48hr     40
4   96hr     50
>>> from natsort import index_natsorted
>>> df.sort_values(
...    by="time",
...    key=lambda x: np.argsort(index_natsorted(df["time"]))
... )
    time  value
0    0hr     10
3   48hr     40
2   72hr     30
4   96hr     50
1  128hr     20
```

pandas.DataFrame.sparse

DataFrame.**sparse**()

DataFrame accessor for sparse data.

New in version 0.25.0.

pandas.DataFrame.squeeze

DataFrame.**squeeze**(*axis=None*)

Squeeze 1 dimensional axis objects into scalars.

Series or DataFrames with a single element are squeezed to a scalar. DataFrames with a single column or a single row are squeezed to a Series. Otherwise the object is unchanged.

This method is most useful when you don't know if your object is a Series or DataFrame, but you do know it has just a single column. In that case you can safely call *squeeze* to ensure you have a Series.

Parameters

axis [{0 or 'index', 1 or 'columns', None}, default None] A specific axis to squeeze. By default, all length-1 axes are squeezed.

Returns

DataFrame, Series, or scalar The projection after squeezing *axis* or all the axes.

See also:

Series.iloc Integer-location based indexing for selecting scalars.

DataFrame.iloc Integer-location based indexing for selecting Series.

Series.to_frame Inverse of DataFrame.squeeze for a single-column DataFrame.

Examples

```
>>> primes = pd.Series([2, 3, 5, 7])
```

Slicing might produce a Series with a single value:

```
>>> even_primes = primes[primes % 2 == 0]
>>> even_primes
0    2
dtype: int64
```

```
>>> even_primes.squeeze()
2
```

Squeezing objects with more than one value in every axis does nothing:

```
>>> odd_primes = primes[primes % 2 == 1]
>>> odd_primes
1    3
2    5
3    7
dtype: int64
```

```
>>> odd_primes.squeeze()
1    3
2    5
3    7
dtype: int64
```

Squeezing is even more effective when used with DataFrames.

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=['a', 'b'])
>>> df
   a  b
0  1  2
1  3  4
```

Slicing a single column will produce a DataFrame with the columns having only one value:

```
>>> df_a = df[['a']]
>>> df_a
   a
0  1
1  3
```

So the columns can be squeezed down, resulting in a Series:

```
>>> df_a.squeeze('columns')
0    1
1    3
Name: a, dtype: int64
```

Slicing a single row from a single column will produce a single scalar DataFrame:

```
>>> df_0a = df.loc[df.index < 1, ['a']]
>>> df_0a
   a
0  1
```

Squeezing the rows produces a single scalar Series:

```
>>> df_0a.squeeze('rows')
a    1
Name: 0, dtype: int64
```

Squeezing all axes will project directly into a scalar:

```
>>> df_0a.squeeze()
1
```

pandas.DataFrame.stack

DataFrame.**stack**(*level=-1*, *dropna=True*)

Stack the prescribed level(s) from columns to index.

Return a reshaped DataFrame or Series having a multi-level index with one or more new inner-most levels compared to the current DataFrame. The new inner-most levels are created by pivoting the columns of the current dataframe:

- if the columns have a single level, the output is a Series;
- if the columns have multiple levels, the new index level(s) is (are) taken from the prescribed level(s) and the output is a DataFrame.

Parameters

level [int, str, list, default -1] Level(s) to stack from the column axis onto the index axis, defined as one index or label, or a list of indices or labels.

dropna [bool, default True] Whether to drop rows in the resulting Frame/Series with missing values. Stacking a column level onto the index axis can create combinations of index and column values that are missing from the original dataframe. See Examples section.

Returns

DataFrame or Series Stacked dataframe or series.

See also:

DataFrame.unstack Unstack prescribed level(s) from index axis onto column axis.

DataFrame.pivot Reshape dataframe from long format to wide format.

DataFrame.pivot_table Create a spreadsheet-style pivot table as a DataFrame.

Notes

The function is named by analogy with a collection of books being reorganized from being side by side on a horizontal position (the columns of the dataframe) to being stacked vertically on top of each other (in the index of the dataframe).

Examples

Single level columns

```
>>> df_single_level_cols = pd.DataFrame([[0, 1], [2, 3]],
...                                     index=['cat', 'dog'],
...                                     columns=['weight', 'height'])
```

Stacking a dataframe with a single level column axis returns a Series:

```
>>> df_single_level_cols
     weight height
cat       0      1
dog       2      3
>>> df_single_level_cols.stack()
```

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```
cat  weight    0
     height    1
dog  weight    2
     height    3
dtype: int64
```

Multi level columns: simple case

```
>>> multicol1 = pd.MultiIndex.from_tuples([('weight', 'kg'),
...                                        ('weight', 'pounds')])
>>> df_multi_level_cols1 = pd.DataFrame([[1, 2], [2, 4]],
...                                     index=['cat', 'dog'],
...                                     columns=multicol1)
```

Stacking a dataframe with a multi-level column axis:

```
>>> df_multi_level_cols1
     weight
         kg    pounds
cat       1         2
dog       2         4
>>> df_multi_level_cols1.stack()
            weight
cat kg           1
    pounds       2
dog kg           2
    pounds       4
```

Missing values

```
>>> multicol2 = pd.MultiIndex.from_tuples([('weight', 'kg'),
...                                        ('height', 'm')])
>>> df_multi_level_cols2 = pd.DataFrame([[1.0, 2.0], [3.0, 4.0]],
...                                     index=['cat', 'dog'],
...                                     columns=multicol2)
```

It is common to have missing values when stacking a dataframe with multi-level columns, as the stacked dataframe typically has more values than the original dataframe. Missing values are filled with NaNs:

```
>>> df_multi_level_cols2
    weight height
        kg      m
cat    1.0    2.0
dog    3.0    4.0
>>> df_multi_level_cols2.stack()
        height  weight
cat kg     NaN     1.0
    m      2.0     NaN
dog kg     NaN     3.0
    m      4.0     NaN
```

Prescribing the level(s) to be stacked

The first parameter controls which level or levels are stacked:

```
>>> df_multi_level_cols2.stack(0)
             kg    m
```

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```
cat height  NaN  2.0
    weight  1.0  NaN
dog height  NaN  4.0
    weight  3.0  NaN
>>> df_multi_level_cols2.stack([0, 1])
cat  height  m     2.0
     weight  kg    1.0
dog  height  m     4.0
     weight  kg    3.0
dtype: float64
```

Dropping missing values

```
>>> df_multi_level_cols3 = pd.DataFrame([[None, 1.0], [2.0, 3.0]],
...                                     index=['cat', 'dog'],
...                                     columns=multicol2)
```

Note that rows where all values are missing are dropped by default but this behaviour can be controlled via the dropna keyword parameter:

```
>>> df_multi_level_cols3
    weight height
        kg      m
cat    NaN    1.0
dog    2.0    3.0
>>> df_multi_level_cols3.stack(dropna=False)
        height  weight
cat kg     NaN     NaN
    m      1.0     NaN
dog kg     NaN     2.0
    m      3.0     NaN
>>> df_multi_level_cols3.stack(dropna=True)
        height  weight
cat m      1.0     NaN
dog kg     NaN     2.0
    m      3.0     NaN
```

pandas.DataFrame.std

DataFrame.**std**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return sample standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis [{index (0), columns (1)}]

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

Series or DataFrame (if level specified)

Notes

To have the same behaviour as *numpy.std*, use *ddof=0* (instead of the default *ddof=1*)

pandas.DataFrame.sub

`DataFrame.`**`sub`**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Subtraction of dataframe and other, element-wise (binary operator *sub*).

Equivalent to `dataframe - other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rsub*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.subtract

DataFrame.**subtract**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Subtraction of dataframe and other, element-wise (binary operator *sub*).

Equivalent to `dataframe - other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rsub*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...        axis='index')
           angles  degrees
```

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```
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.sum

DataFrame.**sum**(*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, *min_count=0*, ***kwargs*)

Return the sum of the values over the requested axis.

This is equivalent to the method `numpy.sum`.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

See also:

Series.sum Return the sum.

Series.min Return the minimum.

Series.max Return the maximum.

Series.idxmin Return the index of the minimum.

Series.idxmax Return the index of the maximum.

DataFrame.sum Return the sum over the requested axis.

DataFrame.min Return the minimum over the requested axis.

DataFrame.max Return the maximum over the requested axis.

DataFrame.idxmin Return the index of the minimum over the requested axis.

DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded  animal
warm     dog       4
```

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```
         falcon    2
cold     fish      0
         spider    8
Name: legs, dtype: int64
```

```
>>> s.sum()
14
```

Sum using level names, as well as indices.

```
>>> s.sum(level='blooded')
blooded
warm    6
cold    8
Name: legs, dtype: int64
```

```
>>> s.sum(level=0)
blooded
warm    6
cold    8
Name: legs, dtype: int64
```

By default, the sum of an empty or all-NA Series is `0`.

```
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the `min_count` parameter. For example, if you'd like the sum of an empty series to be NaN, pass `min_count=1`.

```
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).sum()
0.0
```

```
>>> pd.Series([np.nan]).sum(min_count=1)
nan
```

pandas.DataFrame.swapaxes

DataFrame.**swapaxes**(*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately.

Returns

y [same as input]

pandas.DataFrame.swaplevel

DataFrame.**swaplevel**(*i=-2*, *j=-1*, *axis=0*)

Swap levels i and j in a MultiIndex on a particular axis.

Parameters

i, j [int or str] Levels of the indices to be swapped. Can pass level name as string.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to swap levels on. 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

Returns

DataFrame

pandas.DataFrame.tail

DataFrame.**tail**(*n=5*)

Return the last *n* rows.

This function returns last *n* rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.

For negative values of *n*, this function returns all rows except the first *n* rows, equivalent to `df[n:]`.

Parameters

n [int, default 5] Number of rows to select.

Returns

type of caller The last *n* rows of the caller object.

See also:

DataFrame.head The first *n* rows of the caller object.

Examples

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                    'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
      animal
0  alligator
1        bee
2     falcon
3       lion
4     monkey
5     parrot
6      shark
7      whale
8      zebra
```

Viewing the last 5 lines

```
>>> df.tail()
   animal
4  monkey
5  parrot
6   shark
7   whale
8   zebra
```

Viewing the last *n* lines (three in this case)

```
>>> df.tail(3)
  animal
6  shark
7  whale
8  zebra
```

For negative values of *n*

```
>>> df.tail(-3)
   animal
3    lion
4  monkey
5  parrot
6   shark
7   whale
8   zebra
```

pandas.DataFrame.take

DataFrame.**take**(*indices*, *axis=0*, *is_copy=None*, ***kwargs*)

Return the elements in the given *positional* indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

Parameters

indices [array-like] An array of ints indicating which positions to take.

axis [{0 or 'index', 1 or 'columns', None}, default 0] The axis on which to select elements. `0` means that we are selecting rows, `1` means that we are selecting columns.

is_copy [bool] Before pandas 1.0, `is_copy=False` can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, `take` always returns a copy, and the keyword is therefore deprecated.

Deprecated since version 1.0.0.

****kwargs** For compatibility with `numpy.take()`. Has no effect on the output.

Returns

taken [same type as caller] An array-like containing the elements taken from the object.

See also:

DataFrame.loc Select a subset of a DataFrame by labels.

DataFrame.iloc Select a subset of a DataFrame by positions.

numpy.take Take elements from an array along an axis.

Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                    ('parrot', 'bird', 24.0),
...                    ('lion', 'mammal', 80.5),
...                    ('monkey', 'mammal', np.nan)],
...                   columns=['name', 'class', 'max_speed'],
...                   index=[0, 2, 3, 1])
>>> df
     name   class  max_speed
0  falcon    bird      389.0
2  parrot    bird       24.0
3    lion  mammal       80.5
1  monkey  mammal        NaN
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```
>>> df.take([0, 3])
     name   class  max_speed
0  falcon    bird      389.0
1  monkey  mammal        NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```
>>> df.take([1, 2], axis=1)
    class  max_speed
0    bird      389.0
2    bird       24.0
3  mammal       80.5
1  mammal        NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```
>>> df.take([-1, -2])
     name   class  max_speed
1  monkey  mammal        NaN
3    lion  mammal       80.5
```

pandas.DataFrame.to_clipboard

DataFrame.**to_clipboard**(*excel=True*, *sep=None*, ***kwargs*)

Copy object to the system clipboard.

Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

Parameters

excel [bool, default True] Produce output in a csv format for easy pasting into excel.

- True, use the provided separator for csv pasting.

- False, write a string representation of the object to the clipboard.

sep [str, default `'\t'`] Field delimiter.

****kwargs** These parameters will be passed to DataFrame.to_csv.

See also:

DataFrame.to_csv Write a DataFrame to a comma-separated values (csv) file.

read_clipboard Read text from clipboard and pass to read_table.

Notes

Requirements for your platform.

- Linux : *xclip*, or *xsel* (with *PyQt4* modules)
- Windows : none
- OS X : none

Examples

Copy the contents of a DataFrame to the clipboard.

```
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
```

```
>>> df.to_clipboard(sep=',')
... # Wrote the following to the system clipboard:
... # ,A,B,C
... # 0,1,2,3
... # 1,4,5,6
```

We can omit the index by passing the keyword *index* and setting it to false.

```
>>> df.to_clipboard(sep=',', index=False)
... # Wrote the following to the system clipboard:
... # A,B,C
... # 1,2,3
... # 4,5,6
```

pandas.DataFrame.to_csv

DataFrame.**to_csv**(*path_or_buf=None*, *sep=','*, *na_rep=''*, *float_format=None*, *columns=None*, *header=True*, *index=True*, *index_label=None*, *mode='w'*, *encoding=None*, *compression='infer'*, *quoting=None*, *quotechar='"'*, *line_terminator=None*, *chunksize=None*, *date_format=None*, *doublequote=True*, *escapechar=None*, *decimal='.'*, *errors='strict'*, *storage_options=None*)

Write object to a comma-separated values (csv) file.

Changed in version 0.24.0: The order of arguments for Series was changed.

Parameters

path_or_buf [str or file handle, default None] File path or object, if None is provided the result is returned as a string. If a non-binary file object is passed, it should be opened with *newline=''*, disabling universal newlines. If a binary file object is passed, *mode* might need to contain a *'b'*.

Changed in version 0.24.0: Was previously named "path" for Series.

Changed in version 1.2.0: Support for binary file objects was introduced.

sep [str, default ','] String of length 1. Field delimiter for the output file.

na_rep [str, default ''] Missing data representation.

float_format [str, default None] Format string for floating point numbers.

columns [sequence, optional] Columns to write.

header [bool or list of str, default True] Write out the column names. If a list of strings is given it is assumed to be aliases for the column names.

Changed in version 0.24.0: Previously defaulted to False for Series.

index [bool, default True] Write row names (index).

index_label [str or sequence, or False, default None] Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the object uses MultiIndex. If False do not print fields for index names. Use index_label=False for easier importing in R.

mode [str] Python write mode, default 'w'.

encoding [str, optional] A string representing the encoding to use in the output file, defaults to 'utf-8'. *encoding* is not supported if *path_or_buf* is a non-binary file object.

compression [str or dict, default 'infer'] If str, represents compression mode. If dict, value at 'method' is the compression mode. Compression mode may be any of the following possible values: {'infer', 'gzip', 'bz2', 'zip', 'xz', None}. If compression mode is 'infer' and *path_or_buf* is path-like, then detect compression mode from the following extensions: '.gz', '.bz2', '.zip' or '.xz'. (otherwise no compression). If dict given and mode is one of {'zip', 'gzip', 'bz2'}, or inferred as one of the above, other entries passed as additional compression options.

Changed in version 1.0.0: May now be a dict with key 'method' as compression mode and other entries as additional compression options if compression mode is 'zip'.

Changed in version 1.1.0: Passing compression options as keys in dict is supported for compression modes 'gzip' and 'bz2' as well as 'zip'.

Changed in version 1.2.0: Compression is supported for binary file objects.

Changed in version 1.2.0: Previous versions forwarded dict entries for 'gzip' to *gzip.open* instead of *gzip.GzipFile* which prevented setting *mtime*.

quoting [optional constant from csv module] Defaults to csv.QUOTE_MINIMAL. If you have set a *float_format* then floats are converted to strings and thus csv.QUOTE_NONNUMERIC will treat them as non-numeric.

quotechar [str, default '"'] String of length 1. Character used to quote fields.

line_terminator [str, optional] The newline character or character sequence to use in the output file. Defaults to *os.linesep*, which depends on the OS in which this method is called ('n' for linux, 'rn' for Windows, i.e.).

Changed in version 0.24.0.

chunksize [int or None] Rows to write at a time.

date_format [str, default None] Format string for datetime objects.

doublequote [bool, default True] Control quoting of *quotechar* inside a field.

escapechar [str, default None] String of length 1. Character used to escape *sep* and *quotechar* when appropriate.

decimal [str, default '.'] Character recognized as decimal separator. E.g. use ',' for European data.

errors [str, default 'strict'] Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.

New in version 1.1.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

None or str If path_or_buf is None, returns the resulting csv format as a string. Otherwise returns None.

See also:

read_csv Load a CSV file into a DataFrame.

to_excel Write DataFrame to an Excel file.

Examples

```
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
...                    'mask': ['red', 'purple'],
...                    'weapon': ['sai', 'bo staff']})
>>> df.to_csv(index=False)
'name,mask,weapon\nRaphael,red,sai\nDonatello,purple,bo staff\n'
```

Create 'out.zip' containing 'out.csv'

```
>>> compression_opts = dict(method='zip',
...                         archive_name='out.csv')
>>> df.to_csv('out.zip', index=False,
...           compression=compression_opts)
```

pandas.DataFrame.to_dict

DataFrame.**to_dict**(*orient='dict'*, *into=<class 'dict'>*)

Convert the DataFrame to a dictionary.

The type of the key-value pairs can be customized with the parameters (see below).

Parameters

orient [str {'dict', 'list', 'series', 'split', 'records', 'index'}] Determines the type of the values of the dictionary.

- 'dict' (default) : dict like {column -> {index -> value}}
- 'list' : dict like {column -> [values]}
- 'series' : dict like {column -> Series(values)}
- 'split' : dict like {'index' -> [index], 'columns' -> [columns], 'data' -> [values]}
- 'records' : list like [{column -> value}, ... , {column -> value}]
- 'index' : dict like {index -> {column -> value}}

Abbreviations are allowed. *s* indicates *series* and *sp* indicates *split*.

into [class, default dict] The collections.abc.Mapping subclass used for all Mappings in the return value. Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.

Returns

dict, list or collections.abc.Mapping Return a collections.abc.Mapping object representing the DataFrame. The resulting transformation depends on the *orient* parameter.

See also:

DataFrame.from_dict Create a DataFrame from a dictionary.

DataFrame.to_json Convert a DataFrame to JSON format.

Examples

```
>>> df = pd.DataFrame({'col1': [1, 2],
...                    'col2': [0.5, 0.75]},
...                   index=['row1', 'row2'])
>>> df
      col1  col2
row1     1  0.50
row2     2  0.75
>>> df.to_dict()
{'col1': {'row1': 1, 'row2': 2}, 'col2': {'row1': 0.5, 'row2': 0.75}}
```

You can specify the return orientation.

```
>>> df.to_dict('series')
{'col1': row1    1
         row2    2
Name: col1, dtype: int64,
```

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```
'col2': row1    0.50
        row2    0.75
Name: col2, dtype: float64}
```

```
>>> df.to_dict('split')
{'index': ['row1', 'row2'], 'columns': ['col1', 'col2'],
 'data': [[1, 0.5], [2, 0.75]]}
```

```
>>> df.to_dict('records')
[{'col1': 1, 'col2': 0.5}, {'col1': 2, 'col2': 0.75}]
```

```
>>> df.to_dict('index')
{'row1': {'col1': 1, 'col2': 0.5}, 'row2': {'col1': 2, 'col2': 0.75}}
```

You can also specify the mapping type.

```
>>> from collections import OrderedDict, defaultdict
>>> df.to_dict(into=OrderedDict)
OrderedDict([('col1', OrderedDict([('row1', 1), ('row2', 2)])),
             ('col2', OrderedDict([('row1', 0.5), ('row2', 0.75)]))])
```

If you want a *defaultdict*, you need to initialize it:

```
>>> dd = defaultdict(list)
>>> df.to_dict('records', into=dd)
[defaultdict(<class 'list'>, {'col1': 1, 'col2': 0.5}),
 defaultdict(<class 'list'>, {'col1': 2, 'col2': 0.75})]
```

pandas.DataFrame.to_excel

DataFrame.**to_excel**(*excel_writer*, *sheet_name='Sheet1'*, *na_rep=''*, *float_format=None*, *columns=None*, *header=True*, *index=True*, *index_label=None*, *startrow=0*, *startcol=0*, *engine=None*, *merge_cells=True*, *encoding=None*, *inf_rep='inf'*, *verbose=True*, *freeze_panes=None*, *storage_options=None*)

Write object to an Excel sheet.

To write a single object to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an *ExcelWriter* object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique *sheet_name*. With all data written to the file it is necessary to save the changes. Note that creating an *ExcelWriter* object with a file name that already exists will result in the contents of the existing file being erased.

Parameters

excel_writer [path-like, file-like, or ExcelWriter object] File path or existing ExcelWriter.

sheet_name [str, default 'Sheet1'] Name of sheet which will contain DataFrame.

na_rep [str, default ''] Missing data representation.

float_format [str, optional] Format string for floating point numbers. For example `float_format="%.2f"` will format 0.1234 to 0.12.

columns [sequence or list of str, optional] Columns to write.

header [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

index_label [str or sequence, optional] Column label for index column(s) if desired. If not specified, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow [int, default 0] Upper left cell row to dump data frame.

startcol [int, default 0] Upper left cell column to dump data frame.

engine [str, optional] Write engine to use, 'openpyxl' or 'xlsxwriter'. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

Deprecated since version 1.2.0: As the xlwt package is no longer maintained, the `xlwt` engine will be removed in a future version of pandas.

merge_cells [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

encoding [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep [str, default 'inf'] Representation for infinity (there is no native representation for infinity in Excel).

verbose [bool, default True] Display more information in the error logs.

freeze_panes [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

See also:

to_csv Write DataFrame to a comma-separated values (csv) file.

ExcelWriter Class for writing DataFrame objects into excel sheets.

read_excel Read an Excel file into a pandas DataFrame.

read_csv Read a comma-separated values (csv) file into DataFrame.

Notes

For compatibility with *to_csv()*, to_excel serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

Examples

Create, write to and save a workbook:

```
>>> df1 = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                    index=['row 1', 'row 2'],
...                    columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```
>>> df1.to_excel("output.xlsx",
...              sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:

```
>>> with pd.ExcelWriter('output.xlsx',
...                     mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the *engine* keyword (the default engine is automatically chosen depending on the file extension):

```
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

pandas.DataFrame.to_feather

DataFrame.**to_feather**(*path*, ***kwargs*)

Write a DataFrame to the binary Feather format.

Parameters

path [str or file-like object] If a string, it will be used as Root Directory path.

****kwargs** Additional keywords passed to *pyarrow.feather.write_feather()*. Starting with pyarrow 0.17, this includes the *compression*, *compression_level*, *chunksize* and *version* keywords.

New in version 1.1.0.

pandas.DataFrame.to_gbq

DataFrame.**to_gbq**(*destination_table*, *project_id=None*, *chunksize=None*, *reauth=False*, *if_exists='fail'*, *auth_local_webserver=False*, *table_schema=None*, *location=None*, *progress_bar=True*, *credentials=None*)

Write a DataFrame to a Google BigQuery table.

This function requires the pandas-gbq package.

See the How to authenticate with Google BigQuery guide for authentication instructions.

Parameters

destination_table [str] Name of table to be written, in the form `dataset.tablename`.

project_id [str, optional] Google BigQuery Account project ID. Optional when available from the environment.

chunksize [int, optional] Number of rows to be inserted in each chunk from the dataframe. Set to `None` to load the whole dataframe at once.

reauth [bool, default False] Force Google BigQuery to re-authenticate the user. This is useful if multiple accounts are used.

if_exists [str, default 'fail'] Behavior when the destination table exists. Value can be one of:

`'fail'` If table exists raise pandas_gbq.gbq.TableCreationError.

`'replace'` If table exists, drop it, recreate it, and insert data.

`'append'` If table exists, insert data. Create if does not exist.

auth_local_webserver [bool, default False] Use the local webserver flow instead of the console flow when getting user credentials.

New in version 0.2.0 of pandas-gbq.

table_schema [list of dicts, optional] List of BigQuery table fields to which according DataFrame columns conform to, e.g. `[{'name': 'col1', 'type': 'STRING'},...]`. If schema is not provided, it will be generated according to dtypes of DataFrame columns. See BigQuery API documentation on available names of a field.

New in version 0.3.1 of pandas-gbq.

location [str, optional] Location where the load job should run. See the BigQuery locations documentation for a list of available locations. The location must match that of the target dataset.

New in version 0.5.0 of pandas-gbq.

progress_bar [bool, default True] Use the library *tqdm* to show the progress bar for the upload, chunk by chunk.

New in version 0.5.0 of pandas-gbq.

credentials [google.auth.credentials.Credentials, optional] Credentials for accessing Google APIs. Use this parameter to override default credentials, such as to use Compute Engine `google.auth.compute_engine.Credentials` or Service Account `google.oauth2.service_account.Credentials` directly.

New in version 0.8.0 of pandas-gbq.

New in version 0.24.0.

See also:

`pandas_gbq.to_gbq` This function in the pandas-gbq library.

`read_gbq` Read a DataFrame from Google BigQuery.

pandas.DataFrame.to_hdf

DataFrame.**to_hdf**(*path_or_buf*, *key*, *mode='a'*, *complevel=None*, *complib=None*, *append=False*, *format=None*, *index=True*, *min_itemsize=None*, *nan_rep=None*, *dropna=None*, *data_columns=None*, *errors='strict'*, *encoding='UTF-8'*)

Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different a key.

For more information see the *user guide*.

Parameters

path_or_buf [str or pandas.HDFStore] File path or HDFStore object.

key [str] Identifier for the group in the store.

mode [{'a', 'w', 'r+'}, default 'a'] Mode to open file:

- 'w': write, a new file is created (an existing file with the same name would be deleted).
- 'a': append, an existing file is opened for reading and writing, and if the file does not exist it is created.
- 'r+': similar to 'a', but the file must already exist.

complevel [{0-9}, optional] Specifies a compression level for data. A value of 0 disables compression.

complib [{'zlib', 'lzo', 'bzip2', 'blosc'}, default 'zlib'] Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: 'blosc:blosclz'): {'blosc:blosclz', 'blosc:lz4', 'blosc:lz4hc', 'blosc:snappy', 'blosc:zlib', 'blosc:zstd'}. Specifying a compression library which is not available issues a ValueError.

append [bool, default False] For Table formats, append the input data to the existing.

format [{'fixed', 'table', None}, default 'fixed'] Possible values:

- 'fixed': Fixed format. Fast writing/reading. Not-appendable, nor searchable.
- 'table': Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
- If None, pd.get_option('io.hdf.default_format') is checked, followed by fallback to "fixed"

errors [str, default 'strict'] Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.

encoding [str, default "UTF-8"]

min_itemsize [dict or int, optional] Map column names to minimum string sizes for columns.

nan_rep [Any, optional] How to represent null values as str. Not allowed with append=True.

data_columns [list of columns or True, optional] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See *Query via data columns*. Applicable only to format='table'.

See also:

`DataFrame.read_hdf` Read from HDF file.

`DataFrame.to_parquet` Write a DataFrame to the binary parquet format.

`DataFrame.to_sql` Write to a sql table.

`DataFrame.to_feather` Write out feather-format for DataFrames.

`DataFrame.to_csv` Write out to a csv file.

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},
...                   index=['a', 'b', 'c'])
>>> df.to_hdf('data.h5', key='df', mode='w')
```

We can add another object to the same file:

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```
>>> pd.read_hdf('data.h5', 'df')
A  B
a  1  4
b  2  5
c  3  6
>>> pd.read_hdf('data.h5', 's')
0    1
1    2
2    3
3    4
dtype: int64
```

Deleting file with data:

```
>>> import os
>>> os.remove('data.h5')
```

pandas.DataFrame.to_html

DataFrame.**to_html**(*buf=None*, *columns=None*, *col_space=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *justify=None*, *max_rows=None*, *max_cols=None*, *show_dimensions=False*, *decimal='.'*, *bold_rows=True*, *classes=None*, *escape=True*, *notebook=False*, *border=None*, *table_id=None*, *render_links=False*, *encoding=None*)

Render a DataFrame as an HTML table.

Parameters

buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

columns [sequence, optional, default None] The subset of columns to write. Writes all columns by default.

col_space [str or int, list or dict of int or str, optional] The minimum width of each column in CSS length units. An int is assumed to be px units.

New in version 0.25.0: Ability to use str.

header [bool, optional] Whether to print column labels, default True.

index [bool, optional, default True] Whether to print index (row) labels.

na_rep [str, optional, default 'NaN'] String representation of `NaN` to use.

formatters [list, tuple or dict of one-param. functions, optional] Formatter functions to apply to columns' elements by position or name. The result of each function must be a unicode string. List/tuple must be of length equal to the number of columns.

float_format [one-parameter function, optional, default None] Formatter function to apply to columns' elements if they are floats. This function must return a unicode string and will be applied only to the non-`NaN` elements, with `NaN` being handled by `na_rep`.

Changed in version 1.2.0.

sparsify [bool, optional, default True] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row.

index_names [bool, optional, default True] Prints the names of the indexes.

justify [str, default None] How to justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box. Valid values are

- left
- right
- center
- justify
- justify-all
- start
- end
- inherit

- match-parent
- initial
- unset.

max_rows [int, optional] Maximum number of rows to display in the console.

min_rows [int, optional] The number of rows to display in the console in a truncated repr (when number of rows is above *max_rows*).

max_cols [int, optional] Maximum number of columns to display in the console.

show_dimensions [bool, default False] Display DataFrame dimensions (number of rows by number of columns).

decimal [str, default '.'] Character recognized as decimal separator, e.g. ',' in Europe.

bold_rows [bool, default True] Make the row labels bold in the output.

classes [str or list or tuple, default None] CSS class(es) to apply to the resulting html table.

escape [bool, default True] Convert the characters <, >, and & to HTML-safe sequences.

notebook [{True, False}, default False] Whether the generated HTML is for IPython Notebook.

border [int] A `border=border` attribute is included in the opening <*table*> tag. Default `pd.options.display.html.border`.

encoding [str, default "utf-8"] Set character encoding.

New in version 1.0.

table_id [str, optional] A css id is included in the opening <*table*> tag if specified.

render_links [bool, default False] Convert URLs to HTML links.

New in version 0.24.0.

Returns

str or None If buf is None, returns the result as a string. Otherwise returns None.

See also:

to_string Convert DataFrame to a string.

pandas.DataFrame.to_json

DataFrame.**to_json**(*path_or_buf=None*, *orient=None*, *date_format=None*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*, *lines=False*, *compression='infer'*, *index=True*, *indent=None*, *storage_options=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters

path_or_buf [str or file handle, optional] File path or object. If not specified, the result is returned as a string.

orient [str] Indication of expected JSON string format.

- Series:
  - default is 'index'
  - allowed values are: {'split', 'records', 'index', 'table'}.
- DataFrame:
  - default is 'columns'
  - allowed values are: {'split', 'records', 'index', 'columns', 'values', 'table'}.
- The format of the JSON string:
  - 'split' : dict like {'index' -> [index], 'columns' -> [columns], 'data' -> [values]}
  - 'records' : list like [{column -> value}, ... , {column -> value}]
  - 'index' : dict like {index -> {column -> value}}
  - 'columns' : dict like {column -> {index -> value}}
  - 'values' : just the values array
  - 'table' : dict like {'schema': {schema}, 'data': {data}}

  Describing the data, where data component is like `orient='records'`.

date_format [{None, 'epoch', 'iso'}] Type of date conversion. 'epoch' = epoch milliseconds, 'iso' = ISO8601. The default depends on the *orient*. For `orient='table'`, the default is 'iso'. For all other orients, the default is 'epoch'.

double_precision [int, default 10] The number of decimal places to use when encoding floating point values.

force_ascii [bool, default True] Force encoded string to be ASCII.

date_unit [str, default 'ms' (milliseconds)] The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler [callable, default None] Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

lines [bool, default False] If 'orient' is 'records' write out line delimited json format. Will throw ValueError if incorrect 'orient' since others are not list like.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}] A string representing the compression to use in the output file, only used when the first argument is a filename. By default, the compression is inferred from the filename.

Changed in version 0.24.0: 'infer' option added and set to default

index [bool, default True] Whether to include the index values in the JSON string. Not including the index (`index=False`) is only supported when orient is 'split' or 'table'.

indent [int, optional] Length of whitespace used to indent each record.

New in version 1.0.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Returns

None or str If path_or_buf is None, returns the resulting json format as a string. Otherwise returns None.

See also:

read_json Convert a JSON string to pandas object.

Notes

The behavior of `indent=0` varies from the stdlib, which does not indent the output but does insert newlines. Currently, `indent=0` and the default `indent=None` are equivalent in pandas, though this may change in a future release.

`orient='table'` contains a 'pandas_version' field under 'schema'. This stores the version of *pandas* used in the latest revision of the schema.

Examples

```
>>> import json
>>> df = pd.DataFrame(
...     [["a", "b"], ["c", "d"]],
...     index=["row 1", "row 2"],
...     columns=["col 1", "col 2"],
... )
```

```
>>> result = df.to_json(orient="split")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "columns": [
        "col 1",
        "col 2"
    ],
    "index": [
        "row 1",
        "row 2"
    ],
    "data": [
        [
            "a",
            "b"
        ],
        [
            "c",
            "d"
        ]
```

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```
    ]
}
```

Encoding/decoding a Dataframe using `'records'` formatted JSON. Note that index labels are not preserved with this encoding.

```
>>> result = df.to_json(orient="records")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
[
    {
        "col 1": "a",
        "col 2": "b"
    },
    {
        "col 1": "c",
        "col 2": "d"
    }
]
```

Encoding/decoding a Dataframe using `'index'` formatted JSON:

```
>>> result = df.to_json(orient="index")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "row 1": {
        "col 1": "a",
        "col 2": "b"
    },
    "row 2": {
        "col 1": "c",
        "col 2": "d"
    }
}
```

Encoding/decoding a Dataframe using `'columns'` formatted JSON:

```
>>> result = df.to_json(orient="columns")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "col 1": {
        "row 1": "a",
        "row 2": "c"
    },
    "col 2": {
        "row 1": "b",
        "row 2": "d"
    }
}
```

Encoding/decoding a Dataframe using `'values'` formatted JSON:

```
>>> result = df.to_json(orient="values")
>>> parsed = json.loads(result)
```

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```
>>> json.dumps(parsed, indent=4)
[
    [
        "a",
        "b"
    ],
    [
        "c",
        "d"
    ]
]
```

Encoding with Table Schema:

```
>>> result = df.to_json(orient="table")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "schema": {
        "fields": [
            {
                "name": "index",
                "type": "string"
            },
            {
                "name": "col 1",
                "type": "string"
            },
            {
                "name": "col 2",
                "type": "string"
            }
        ],
        "primaryKey": [
            "index"
        ],
        "pandas_version": "0.20.0"
    },
    "data": [
        {
            "index": "row 1",
            "col 1": "a",
            "col 2": "b"
        },
        {
            "index": "row 2",
            "col 1": "c",
            "col 2": "d"
        }
    ]
}
```

pandas.DataFrame.to_latex

DataFrame.**to_latex**(*buf=None*, *columns=None*, *col_space=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *bold_rows=False*, *column_format=None*, *longtable=None*, *escape=None*, *encoding=None*, *decimal='.'*, *multicolumn=None*, *multicolumn_format=None*, *multirow=None*, *caption=None*, *label=None*, *position=None*)

Render object to a LaTeX tabular, longtable, or nested table/tabular.

Requires `\usepackage{booktabs}`. The output can be copy/pasted into a main LaTeX document or read from an external file with `\input{table.tex}`.

Changed in version 1.0.0: Added caption and label arguments.

Changed in version 1.2.0: Added position argument, changed meaning of caption argument.

Parameters

buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

columns [list of label, optional] The subset of columns to write. Writes all columns by default.

col_space [int, optional] The minimum width of each column.

header [bool or list of str, default True] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

na_rep [str, default 'NaN'] Missing data representation.

formatters [list of functions or dict of {str: function}, optional] Formatter functions to apply to columns' elements by position or name. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format [one-parameter function or str, optional, default None] Formatter for floating point numbers. For example `float_format="%.2f"` and `float_format="{:0.2f}".format` will both result in 0.1234 being formatted as 0.12.

sparsify [bool, optional] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row. By default, the value will be read from the config module.

index_names [bool, default True] Prints the names of the indexes.

bold_rows [bool, default False] Make the row labels bold in the output.

column_format [str, optional] The columns format as specified in LaTeX table format e.g. 'rcl' for 3 columns. By default, 'l' will be used for all columns except columns of numbers, which default to 'r'.

longtable [bool, optional] By default, the value will be read from the pandas config module. Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your LaTeX preamble.

escape [bool, optional] By default, the value will be read from the pandas config module. When set to False prevents from escaping latex special characters in column names.

encoding [str, optional] A string representing the encoding to use in the output file, defaults to 'utf-8'.

decimal [str, default '.'] Character recognized as decimal separator, e.g. ',' in Europe.

multicolumn [bool, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

multicolumn_format [str, default 'l'] The alignment for multicolumns, similar to *column_format* The default will be read from the config module.

multirow [bool, default False] Use multirow to enhance MultiIndex rows. Requires adding a usepackage{multirow} to your LaTeX preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

caption [str or tuple, optional] Tuple (full_caption, short_caption), which results in `\caption[short_caption]{full_caption}`; if a single string is passed, no short caption will be set.

New in version 1.0.0.

Changed in version 1.2.0: Optionally allow caption to be a tuple `(full_caption, short_caption)`.

label [str, optional] The LaTeX label to be placed inside `\label{}` in the output. This is used with `\ref{}` in the main `.tex` file.

New in version 1.0.0.

position [str, optional] The LaTeX positional argument for tables, to be placed after `\begin{}` in the output.

New in version 1.2.0.

Returns

str or None If buf is None, returns the result as a string. Otherwise returns None.

See also:

DataFrame.to_string Render a DataFrame to a console-friendly tabular output.

DataFrame.to_html Render a DataFrame as an HTML table.

Examples

```
>>> df = pd.DataFrame(dict(name=['Raphael', 'Donatello'],
...                        mask=['red', 'purple'],
...                        weapon=['sai', 'bo staff']))
>>> print(df.to_latex(index=False))
\begin{tabular}{lll}
 \toprule
       name &    mask &    weapon \\
 \midrule
    Raphael &     red &       sai \\
  Donatello &  purple &  bo staff \\
\bottomrule
\end{tabular}
```

pandas.DataFrame.to_markdown

DataFrame.**to_markdown**(*buf=None*, *mode='wt'*, *index=True*, *storage_options=None*, ***kwargs*)

Print DataFrame in Markdown-friendly format.

New in version 1.0.0.

Parameters

buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

mode [str, optional] Mode in which file is opened, "wt" by default.

index [bool, optional, default True] Add index (row) labels.

New in version 1.1.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

****kwargs** These parameters will be passed to tabulate.

Returns

str DataFrame in Markdown-friendly format.

Notes

Requires the tabulate package.

Examples

```
>>> s = pd.Series(["elk", "pig", "dog", "quetzal"], name="animal")
>>> print(s.to_markdown())
|    | animal   |
|---:|:---------|
|  0 | elk      |
|  1 | pig      |
|  2 | dog      |
|  3 | quetzal  |
```

Output markdown with a tabulate option.

```
>>> print(s.to_markdown(tablefmt="grid"))
+----+----------+
|    | animal   |
+====+==========+
|  0 | elk      |
+----+----------+
|  1 | pig      |
+----+----------+
|  2 | dog      |
```

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```
+----+----------+
|  3 | quetzal  |
+----+----------+
```

pandas.DataFrame.to_numpy

DataFrame.**to_numpy**(*dtype=None*, *copy=False*, *na_value=<object object>*)

Convert the DataFrame to a NumPy array.

New in version 0.24.0.

By default, the dtype of the returned array will be the common NumPy dtype of all types in the DataFrame. For example, if the dtypes are `float16` and `float32`, the results dtype will be `float32`. This may require copying data and coercing values, which may be expensive.

Parameters

dtype [str or numpy.dtype, optional] The dtype to pass to `numpy.asarray()`.

copy [bool, default False] Whether to ensure that the returned value is not a view on another array. Note that `copy=False` does not *ensure* that `to_numpy()` is no-copy. Rather, `copy=True` ensure that a copy is made, even if not strictly necessary.

na_value [Any, optional] The value to use for missing values. The default value depends on *dtype* and the dtypes of the DataFrame columns.

New in version 1.1.0.

Returns

numpy.ndarray

See also:

Series.to_numpy Similar method for Series.

Examples

```
>>> pd.DataFrame({"A": [1, 2], "B": [3, 4]}).to_numpy()
array([[1, 3],
       [2, 4]])
```

With heterogeneous data, the lowest common type will have to be used.

```
>>> df = pd.DataFrame({"A": [1, 2], "B": [3.0, 4.5]})
>>> df.to_numpy()
array([[1. , 3. ],
       [2. , 4.5]])
```

For a mix of numeric and non-numeric types, the output array will have object dtype.

```
>>> df['C'] = pd.date_range('2000', periods=2)
>>> df.to_numpy()
array([[1, 3.0, Timestamp('2000-01-01 00:00:00')],
       [2, 4.5, Timestamp('2000-01-02 00:00:00')]], dtype=object)
```

pandas.DataFrame.to_parquet

DataFrame.**to_parquet**(*path=None*, *engine='auto'*, *compression='snappy'*, *index=None*, *partition_cols=None*, *storage_options=None*, ***kwargs*)

Write a DataFrame to the binary parquet format.

This function writes the dataframe as a parquet file. You can choose different parquet backends, and have the option of compression. See *the user guide* for more details.

Parameters

path [str or file-like object, default None] If a string, it will be used as Root Directory path when writing a partitioned dataset. By file-like object, we refer to objects with a write() method, such as a file handle (e.g. via builtin open function) or io.BytesIO. The engine fastparquet does not accept file-like objects. If path is None, a bytes object is returned.

Changed in version 1.2.0.

Previously this was "fname"

engine [{'auto', 'pyarrow', 'fastparquet'}, default 'auto'] Parquet library to use. If 'auto', then the option `io.parquet.engine` is used. The default `io.parquet.engine` behavior is to try 'pyarrow', falling back to 'fastparquet' if 'pyarrow' is unavailable.

compression [{'snappy', 'gzip', 'brotli', None}, default 'snappy'] Name of the compression to use. Use `None` for no compression.

index [bool, default None] If `True`, include the dataframe's index(es) in the file output. If `False`, they will not be written to the file. If `None`, similar to `True` the dataframe's index(es) will be saved. However, instead of being saved as values, the RangeIndex will be stored as a range in the metadata so it doesn't require much space and is faster. Other indexes will be included as columns in the file output.

New in version 0.24.0.

partition_cols [list, optional, default None] Column names by which to partition the dataset. Columns are partitioned in the order they are given. Must be None if path is not a string.

New in version 0.24.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

****kwargs** Additional arguments passed to the parquet library. See *pandas io* for more details.

Returns

bytes if no path argument is provided else None

See also:

read_parquet Read a parquet file.

DataFrame.to_csv Write a csv file.

DataFrame.to_sql Write to a sql table.

DataFrame.to_hdf Write to hdf.

Notes

This function requires either the fastparquet or pyarrow library.

Examples

```
>>> df = pd.DataFrame(data={'col1': [1, 2], 'col2': [3, 4]})
>>> df.to_parquet('df.parquet.gzip',
...               compression='gzip')
>>> pd.read_parquet('df.parquet.gzip')
   col1  col2
0     1     3
1     2     4
```

If you want to get a buffer to the parquet content you can use a io.BytesIO object, as long as you don't use partition_cols, which creates multiple files.

```
>>> import io
>>> f = io.BytesIO()
>>> df.to_parquet(f)
>>> f.seek(0)
0
>>> content = f.read()
```

pandas.DataFrame.to_period

DataFrame.**to_period**(*freq=None*, *axis=0*, *copy=True*)

Convert DataFrame from DatetimeIndex to PeriodIndex.

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed).

Parameters

freq [str, default] Frequency of the PeriodIndex.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to convert (the index by default).

copy [bool, default True] If False then underlying input data is not copied.

Returns

DataFrame with PeriodIndex

pandas.DataFrame.to_pickle

DataFrame.**to_pickle**(*path*, *compression='infer'*, *protocol=5*, *storage_options=None*)

Pickle (serialize) object to file.

Parameters

path [str] File path where the pickled object will be stored.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'] A string representing the compression to use in the output file. By default, infers from the file extension in specified path. Compression mode may be any of the following possible values: {'infer', 'gzip', 'bz2', 'zip', 'xz', None}. If compression mode is 'infer' and path_or_buf is path-like, then detect compression mode from the following extensions: '.gz', '.bz2', '.zip' or '.xz'. (otherwise no compression). If dict given and mode is 'zip' or inferred as 'zip', other entries passed as additional compression options.

protocol [int] Int which indicates which protocol should be used by the pickler, default HIGHEST_PROTOCOL (see [1] paragraph 12.1.2). The possible values are 0, 1, 2, 3, 4, 5. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST_PROTOCOL.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

See also:

read_pickle Load pickled pandas object (or any object) from file.

DataFrame.to_hdf Write DataFrame to an HDF5 file.

DataFrame.to_sql Write DataFrame to a SQL database.

DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Examples

```
>>> original_df = pd.DataFrame({"foo": range(5), "bar": range(5, 10)})
>>> original_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
>>> original_df.to_pickle("./dummy.pkl")
```

```
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0    0    5
1    1    6
```

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```
2    2    7
3    3    8
4    4    9
```

```
>>> import os
>>> os.remove("./dummy.pkl")
```

pandas.DataFrame.to_records

DataFrame.**to_records**(*index=True*, *column_dtypes=None*, *index_dtypes=None*)

Convert DataFrame to a NumPy record array.

Index will be included as the first field of the record array if requested.

Parameters

index [bool, default True] Include index in resulting record array, stored in 'index' field or using the index label, if set.

column_dtypes [str, type, dict, default None] New in version 0.24.0.

If a string or type, the data type to store all columns. If a dictionary, a mapping of column names and indices (zero-indexed) to specific data types.

index_dtypes [str, type, dict, default None] New in version 0.24.0.

If a string or type, the data type to store all index levels. If a dictionary, a mapping of index level names and indices (zero-indexed) to specific data types.

This mapping is applied only if *index=True*.

Returns

numpy.recarray NumPy ndarray with the DataFrame labels as fields and each row of the DataFrame as entries.

See also:

DataFrame.from_records Convert structured or record ndarray to DataFrame.

numpy.recarray An ndarray that allows field access using attributes, analogous to typed columns in a spreadsheet.

Examples

```
>>> df = pd.DataFrame({'A': [1, 2], 'B': [0.5, 0.75]},
...                   index=['a', 'b'])
>>> df
   A     B
a  1  0.50
b  2  0.75
>>> df.to_records()
rec.array([('a', 1, 0.5 ), ('b', 2, 0.75)],
          dtype=[('index', 'O'), ('A', '<i8'), ('B', '<f8')])
```

If the DataFrame index has no label then the recarray field name is set to 'index'. If the index has a label then this is used as the field name:

```
>>> df.index = df.index.rename("I")
>>> df.to_records()
rec.array([('a', 1, 0.5 ), ('b', 2, 0.75)],
          dtype=[('I', 'O'), ('A', '<i8'), ('B', '<f8')])
```

The index can be excluded from the record array:

```
>>> df.to_records(index=False)
rec.array([(1, 0.5 ), (2, 0.75)],
          dtype=[('A', '<i8'), ('B', '<f8')])
```

Data types can be specified for the columns:

```
>>> df.to_records(column_dtypes={"A": "int32"})
rec.array([('a', 1, 0.5 ), ('b', 2, 0.75)],
          dtype=[('I', 'O'), ('A', '<i4'), ('B', '<f8')])
```

As well as for the index:

```
>>> df.to_records(index_dtypes="<S2")
rec.array([(b'a', 1, 0.5 ), (b'b', 2, 0.75)],
          dtype=[('I', 'S2'), ('A', '<i8'), ('B', '<f8')])
```

```
>>> index_dtypes = f"<S{df.index.str.len().max()}"
>>> df.to_records(index_dtypes=index_dtypes)
rec.array([(b'a', 1, 0.5 ), (b'b', 2, 0.75)],
          dtype=[('I', 'S1'), ('A', '<i8'), ('B', '<f8')])
```

pandas.DataFrame.to_sql

DataFrame.**to_sql**(*name*, *con*, *schema=None*, *if_exists='fail'*, *index=True*, *index_label=None*, *chunksize=None*, *dtype=None*, *method=None*)

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [1] are supported. Tables can be newly created, appended to, or overwritten.

Parameters

name [str] Name of SQL table.

con [sqlalchemy.engine.(Engine or Connection) or sqlite3.Connection] Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable See here.

schema [str, optional] Specify the schema (if database flavor supports this). If None, use default schema.

if_exists [{'fail', 'replace', 'append'}, default 'fail'] How to behave if the table already exists.

- fail: Raise a ValueError.
- replace: Drop the table before inserting new values.
- append: Insert new values to the existing table.

index [bool, default True] Write DataFrame index as a column. Uses *index_label* as the column name in the table.

index_label [str or sequence, default None] Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize [int, optional] Specify the number of rows in each batch to be written at a time. By default, all rows will be written at once.

dtype [dict or scalar, optional] Specifying the datatype for columns. If a dictionary is used, the keys should be the column names and the values should be the SQLAlchemy types or strings for the sqlite3 legacy mode. If a scalar is provided, it will be applied to all columns.

method [{None, 'multi', callable}, optional] Controls the SQL insertion clause used:

- None : Uses standard SQL `INSERT` clause (one per row).
- 'multi': Pass multiple values in a single `INSERT` clause.
- callable with signature `(pd_table, conn, keys, data_iter)`.

Details and a sample callable implementation can be found in the section *insert method*.

New in version 0.24.0.

Raises

ValueError When the table already exists and *if_exists* is 'fail' (the default).

See also:

read_sql Read a DataFrame from a table.

Notes

Timezone aware datetime columns will be written as `Timestamp with timezone` type with SQLAlchemy if supported by the database. Otherwise, the datetimes will be stored as timezone unaware timestamps local to the original timezone.

New in version 0.24.0.

References

[1], [2]

Examples

Create an in-memory SQLite database.

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})
>>> df
     name
0  User 1
1  User 2
2  User 3
```

```
>>> df.to_sql('users', con=engine)
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]
```

An *sqlalchemy.engine.Connection* can also be passed to *con*:

```
>>> with engine.begin() as connection:
...     df1 = pd.DataFrame({'name' : ['User 4', 'User 5']})
...     df1.to_sql('users', con=connection, if_exists='append')
```

This is allowed to support operations that require that the same DBAPI connection is used for the entire operation.

```
>>> df2 = pd.DataFrame({'name' : ['User 6', 'User 7']})
>>> df2.to_sql('users', con=engine, if_exists='append')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3'),
 (0, 'User 4'), (1, 'User 5'), (0, 'User 6'),
 (1, 'User 7')]
```

Overwrite the table with just `df2`.

```
>>> df2.to_sql('users', con=engine, if_exists='replace',
...            index_label='id')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 6'), (1, 'User 7')]
```

Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```
>>> df = pd.DataFrame({"A": [1, None, 2]})
>>> df
     A
0  1.0
1  NaN
2  2.0
```

```
>>> from sqlalchemy.types import Integer
>>> df.to_sql('integers', con=engine, index=False,
...           dtype={"A": Integer()})
```

```
>>> engine.execute("SELECT * FROM integers").fetchall()
[(1,), (None,), (2,)]
```

pandas.DataFrame.to_stata

DataFrame.**to_stata**(*path*, *convert_dates=None*, *write_index=True*, *byteorder=None*, *time_stamp=None*, *data_label=None*, *variable_labels=None*, *version=114*, *convert_strl=None*, *compression='infer'*, *storage_options=None*)

Export DataFrame object to Stata dta format.

Writes the DataFrame to a Stata dataset file. "dta" files contain a Stata dataset.

Parameters

path [str, buffer or path object] String, path object (pathlib.Path or py._path.local.LocalPath) or object implementing a binary write() function. If using a buffer then the buffer will not be automatically closed after the file data has been written.

Changed in version 1.0.0.

Previously this was "fname"

convert_dates [dict] Dictionary mapping columns containing datetime types to stata internal format to use when writing the dates. Options are 'tc', 'td', 'tm', 'tw', 'th', 'tq', 'ty'. Column can be either an integer or a name. Datetime columns that do not have a conversion type specified will be converted to 'tc'. Raises NotImplementedError if a datetime column has timezone information.

write_index [bool] Write the index to Stata dataset.

byteorder [str] Can be ">", "<", "little", or "big". default is *sys.byteorder*.

time_stamp [datetime] A datetime to use as file creation date. Default is the current time.

data_label [str, optional] A label for the data set. Must be 80 characters or smaller.

variable_labels [dict] Dictionary containing columns as keys and variable labels as values. Each label must be 80 characters or smaller.

version [{114, 117, 118, 119, None}, default 114] Version to use in the output dta file. Set to None to let pandas decide between 118 or 119 formats depending on the number of columns in the frame. Version 114 can be read by Stata 10 and later. Version 117 can be read by Stata 13 or later. Version 118 is supported in Stata 14 and later. Version 119 is supported in Stata 15 and later. Version 114 limits string variables to 244 characters or fewer while versions 117 and later allow strings with lengths up to 2,000,000 characters. Versions 118 and 119 support Unicode characters, and version 119 supports more than 32,767 variables.

Version 119 should usually only be used when the number of variables exceeds the capacity of dta format 118. Exporting smaller datasets in format 119 may have unintended consequences, and, as of November 2020, Stata SE cannot read version 119 files.

Changed in version 1.0.0: Added support for formats 118 and 119.

convert_strl [list, optional] List of column names to convert to string columns to Stata StrL format. Only available if version is 117. Storing strings in the StrL format can produce smaller dta files if strings have more than 8 characters and values are repeated.

compression [str or dict, default 'infer'] For on-the-fly compression of the output dta. If string, specifies compression mode. If dict, value at key 'method' specifies compression mode. Compression mode must be one of {'infer', 'gzip', 'bz2', 'zip',

'xz', None}. If compression mode is 'infer' and *fname* is path-like, then detect compression from the following extensions: '.gz', '.bz2', '.zip', or '.xz' (otherwise no compression). If dict and compression mode is one of {'zip', 'gzip', 'bz2'}, or inferred as one of the above, other entries passed as additional compression options.

New in version 1.1.0.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

Raises

NotImplementedError

- If datetimes contain timezone information
- Column dtype is not representable in Stata

ValueError

- Columns listed in convert_dates are neither datetime64[ns] or datetime.datetime
- Column listed in convert_dates is not in DataFrame
- Categorical label contains more than 32,000 characters

See also:

read_stata Import Stata data files.

io.stata.StataWriter Low-level writer for Stata data files.

io.stata.StataWriter117 Low-level writer for version 117 files.

Examples

```
>>> df = pd.DataFrame({'animal': ['falcon', 'parrot', 'falcon',
...                               'parrot'],
...                    'speed': [350, 18, 361, 15]})
>>> df.to_stata('animals.dta')
```

pandas.DataFrame.to_string

DataFrame.**to_string**(*buf=None*, *columns=None*, *col_space=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *justify=None*, *max_rows=None*, *min_rows=None*, *max_cols=None*, *show_dimensions=False*, *decimal='.'*, *line_width=None*, *max_colwidth=None*, *encoding=None*)

Render a DataFrame to a console-friendly tabular output.

Parameters

buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

columns [sequence, optional, default None] The subset of columns to write. Writes all columns by default.

col_space [int, list or dict of int, optional] The minimum width of each column.

header [bool or sequence, optional] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.

index [bool, optional, default True] Whether to print index (row) labels.

na_rep [str, optional, default 'NaN'] String representation of `NaN` to use.

formatters [list, tuple or dict of one-param. functions, optional] Formatter functions to apply to columns' elements by position or name. The result of each function must be a unicode string. List/tuple must be of length equal to the number of columns.

float_format [one-parameter function, optional, default None] Formatter function to apply to columns' elements if they are floats. This function must return a unicode string and will be applied only to the non-`NaN` elements, with `NaN` being handled by `na_rep`.

Changed in version 1.2.0.

sparsify [bool, optional, default True] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row.

index_names [bool, optional, default True] Prints the names of the indexes.

justify [str, default None] How to justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box. Valid values are

- left
- right
- center
- justify
- justify-all
- start
- end
- inherit
- match-parent
- initial
- unset.

max_rows [int, optional] Maximum number of rows to display in the console.

min_rows [int, optional] The number of rows to display in the console in a truncated repr (when number of rows is above *max_rows*).

max_cols [int, optional] Maximum number of columns to display in the console.

show_dimensions [bool, default False] Display DataFrame dimensions (number of rows by number of columns).

decimal [str, default '.'] Character recognized as decimal separator, e.g. ',' in Europe.

line_width [int, optional] Width to wrap a line in characters.

max_colwidth [int, optional] Max width to truncate each column in characters. By default, no limit.

New in version 1.0.0.

encoding [str, default "utf-8"] Set character encoding.

New in version 1.0.

Returns

str or None If buf is None, returns the result as a string. Otherwise returns None.

See also:

to_html Convert DataFrame to HTML.

Examples

```
>>> d = {'col1': [1, 2, 3], 'col2': [4, 5, 6]}
>>> df = pd.DataFrame(d)
>>> print(df.to_string())
   col1  col2
0     1     4
1     2     5
2     3     6
```

pandas.DataFrame.to_timestamp

DataFrame.**to_timestamp**(*freq=None*, *how='start'*, *axis=0*, *copy=True*)

Cast to DatetimeIndex of timestamps, at *beginning* of period.

Parameters

freq [str, default frequency of PeriodIndex] Desired frequency.

how [{'s', 'e', 'start', 'end'}] Convention for converting period to timestamp; start of period vs. end.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to convert (the index by default).

copy [bool, default True] If False then underlying input data is not copied.

Returns

DataFrame with DatetimeIndex

pandas.DataFrame.to_xarray

DataFrame.**to_xarray**()

Return an xarray object from the pandas object.

Returns

xarray.DataArray or xarray.Dataset Data in the pandas structure converted to Dataset if the object is a DataFrame, or a DataArray if the object is a Series.

See also:

DataFrame.to_hdf Write DataFrame to an HDF5 file.

DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Notes

See the xarray docs

Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0, 2),
...                    ('parrot', 'bird', 24.0, 2),
...                    ('lion', 'mammal', 80.5, 4),
...                    ('monkey', 'mammal', np.nan, 4)],
...                   columns=['name', 'class', 'max_speed',
...                            'num_legs'])
>>> df
     name   class  max_speed  num_legs
0  falcon    bird      389.0         2
1  parrot    bird       24.0         2
2    lion  mammal       80.5         4
3  monkey  mammal        NaN         4
```

```
>>> df.to_xarray()
<xarray.Dataset>
Dimensions:    (index: 4)
Coordinates:
  * index      (index) int64 0 1 2 3
Data variables:
    name       (index) object 'falcon' 'parrot' 'lion' 'monkey'
    class      (index) object 'bird' 'bird' 'mammal' 'mammal'
    max_speed  (index) float64 389.0 24.0 80.5 nan
    num_legs   (index) int64 2 2 4 4
```

```
>>> df['max_speed'].to_xarray()
<xarray.DataArray 'max_speed' (index: 4)>
array([389. ,  24. ,  80.5,   nan])
Coordinates:
  * index    (index) int64 0 1 2 3
```

```
>>> dates = pd.to_datetime(['2018-01-01', '2018-01-01',
...                         '2018-01-02', '2018-01-02'])
>>> df_multiindex = pd.DataFrame({'date': dates,
```

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```
...                                 'animal': ['falcon', 'parrot',
...                                           'falcon', 'parrot'],
...                                 'speed': [350, 18, 361, 15]})
>>> df_multiindex = df_multiindex.set_index(['date', 'animal'])
```

```
>>> df_multiindex
                   speed
date       animal
2018-01-01 falcon    350
           parrot     18
2018-01-02 falcon    361
           parrot     15
```

```
>>> df_multiindex.to_xarray()
<xarray.Dataset>
Dimensions:  (animal: 2, date: 2)
Coordinates:
  * date     (date) datetime64[ns] 2018-01-01 2018-01-02
  * animal   (animal) object 'falcon' 'parrot'
Data variables:
    speed    (date, animal) int64 350 18 361 15
```

pandas.DataFrame.transform

DataFrame.**transform**(*func*, *axis=0*, **args*, ***kwargs*)

Call `func` on self producing a DataFrame with transformed values.

Produced DataFrame will have same axis length as self.

Parameters

func [function, str, list-like or dict-like] Function to use for transforming the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply. If func is both list-like and dict-like, dict-like behavior takes precedence.

Accepted combinations are:

- function
- string function name
- list-like of functions and/or function names, e.g. `[np.exp, 'sqrt']`
- dict-like of axis labels -> functions, function names or list-like of such.

axis [{0 or 'index', 1 or 'columns'}, default 0] If 0 or 'index': apply function to each column. If 1 or 'columns': apply function to each row.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

DataFrame A DataFrame that must have the same length as self.

Raises

ValueError [If the returned DataFrame has a different length than self.]

See also:

DataFrame.agg Only perform aggregating type operations.

DataFrame.apply Invoke function on a DataFrame.

Examples

```
>>> df = pd.DataFrame({'A': range(3), 'B': range(1, 4)})
>>> df
   A  B
0  0  1
1  1  2
2  2  3
>>> df.transform(lambda x: x + 1)
   A  B
0  1  2
1  2  3
2  3  4
```

Even though the resulting DataFrame must have the same length as the input DataFrame, it is possible to provide several input functions:

```
>>> s = pd.Series(range(3))
>>> s
0    0
1    1
2    2
dtype: int64
>>> s.transform([np.sqrt, np.exp])
       sqrt        exp
0  0.000000   1.000000
1  1.000000   2.718282
2  1.414214   7.389056
```

You can call transform on a GroupBy object:

```
>>> df = pd.DataFrame({
...     "Date": [
...         "2015-05-08", "2015-05-07", "2015-05-06", "2015-05-05",
...         "2015-05-08", "2015-05-07", "2015-05-06", "2015-05-05"],
...     "Data": [5, 8, 6, 1, 50, 100, 60, 120],
... })
>>> df
         Date  Data
0  2015-05-08     5
1  2015-05-07     8
2  2015-05-06     6
3  2015-05-05     1
4  2015-05-08    50
5  2015-05-07   100
6  2015-05-06    60
7  2015-05-05   120
>>> df.groupby('Date')['Data'].transform('sum')
0     55
1    108
2     66
```

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```
3    121
4     55
5    108
6     66
7    121
Name: Data, dtype: int64
```

```
>>> df = pd.DataFrame({
...     "c": [1, 1, 1, 2, 2, 2, 2],
...     "type": ["m", "n", "o", "m", "m", "n", "n"]
... })
>>> df
   c type
0  1    m
1  1    n
2  1    o
3  2    m
4  2    m
5  2    n
6  2    n
>>> df['size'] = df.groupby('c')['type'].transform(len)
>>> df
   c type size
0  1    m    3
1  1    n    3
2  1    o    3
3  2    m    4
4  2    m    4
5  2    n    4
6  2    n    4
```

pandas.DataFrame.transpose

DataFrame.**transpose**(**args*, *copy=False*)

Transpose index and columns.

Reflect the DataFrame over its main diagonal by writing rows as columns and vice-versa. The property *T* is an accessor to the method *transpose()*.

Parameters

***args** [tuple, optional] Accepted for compatibility with NumPy.

copy [bool, default False] Whether to copy the data after transposing, even for DataFrames with a single dtype.

Note that a copy is always required for mixed dtype DataFrames, or for DataFrames with any extension types.

Returns

DataFrame The transposed DataFrame.

See also:

numpy.transpose Permute the dimensions of a given array.

Notes

Transposing a DataFrame with mixed dtypes will result in a homogeneous DataFrame with the *object* dtype. In such a case, a copy of the data is always made.

Examples

Square DataFrame with homogeneous dtype

```
>>> d1 = {'col1': [1, 2], 'col2': [3, 4]}
>>> df1 = pd.DataFrame(data=d1)
>>> df1
   col1  col2
0     1     3
1     2     4
```

```
>>> df1_transposed = df1.T # or df1.transpose()
>>> df1_transposed
      0  1
col1  1  2
col2  3  4
```

When the dtype is homogeneous in the original DataFrame, we get a transposed DataFrame with the same dtype:

```
>>> df1.dtypes
col1    int64
col2    int64
dtype: object
>>> df1_transposed.dtypes
0    int64
1    int64
dtype: object
```

Non-square DataFrame with mixed dtypes

```
>>> d2 = {'name': ['Alice', 'Bob'],
...       'score': [9.5, 8],
...       'employed': [False, True],
...       'kids': [0, 0]}
>>> df2 = pd.DataFrame(data=d2)
>>> df2
    name  score  employed  kids
0  Alice    9.5     False     0
1    Bob    8.0      True     0
```

```
>>> df2_transposed = df2.T # or df2.transpose()
>>> df2_transposed
              0     1
name      Alice   Bob
score       9.5   8.0
employed  False  True
kids          0     0
```

When the DataFrame has mixed dtypes, we get a transposed DataFrame with the *object* dtype:

```
>>> df2.dtypes
name         object
score       float64
employed       bool
kids          int64
dtype: object
>>> df2_transposed.dtypes
0    object
1    object
dtype: object
```

pandas.DataFrame.truediv

DataFrame.**truediv**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Get Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, *rtruediv*.

Among flexible wrappers (*add*, *sub*, *mul*, *div*, *mod*, *pow*) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
circle          0      360
triangle        3      180
rectangle       4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

```
>>> df.add(1)
           angles  degrees
circle          1      361
triangle        4      181
rectangle       5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
           angles  degrees
circle        0.0     36.0
triangle      0.3     18.0
rectangle     0.4     36.0
```

```
>>> df.rdiv(10)
             angles   degrees
circle          inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub([1, 2], axis='columns')
           angles  degrees
circle         -1      358
triangle        2      178
rectangle       3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
           angles  degrees
circle         -1      359
triangle        2      179
rectangle       3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle          0
triangle        3
rectangle       4
```

```
>>> df * other
           angles  degrees
circle          0      NaN
triangle        9      NaN
rectangle      16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles  degrees
circle          0      0.0
triangle        9      0.0
rectangle      16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                              'degrees': [360, 180, 360, 360, 540, 720]},
...                             index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                    ['circle', 'triangle', 'rectangle',
...                                     'square', 'pentagon', 'hexagon']])
>>> df_multindex
             angles  degrees
A circle          0      360
  triangle        3      180
  rectangle       4      360
B square          4      360
  pentagon        5      540
  hexagon         6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
             angles  degrees
A circle        NaN      1.0
  triangle      1.0      1.0
  rectangle     1.0      1.0
B square        0.0      0.0
  pentagon      0.0      0.0
  hexagon       0.0      0.0
```

pandas.DataFrame.truncate

DataFrame.**truncate**(*before=None*, *after=None*, *axis=None*, *copy=True*)

Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

Parameters

before [date, str, int] Truncate all rows before this index value.

after [date, str, int] Truncate all rows after this index value.

axis [{0 or 'index', 1 or 'columns'}, optional] Axis to truncate. Truncates the index (rows) by default.

copy [bool, default is True,] Return a copy of the truncated section.

Returns

type of caller The truncated Series or DataFrame.

See also:

DataFrame.loc Select a subset of a DataFrame by label.

DataFrame.iloc Select a subset of a DataFrame by position.

Notes

If the index being truncated contains only datetime values, *before* and *after* may be specified as strings instead of Timestamps.

Examples

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
...                    'B': ['f', 'g', 'h', 'i', 'j'],
...                    'C': ['k', 'l', 'm', 'n', 'o']},
...                   index=[1, 2, 3, 4, 5])
>>> df
   A  B  C
1  a  f  k
2  b  g  l
3  c  h  m
4  d  i  n
5  e  j  o
```

```
>>> df.truncate(before=2, after=4)
   A  B  C
2  b  g  l
3  c  h  m
4  d  i  n
```

The columns of a DataFrame can be truncated.

```
>>> df.truncate(before="A", after="B", axis="columns")
   A  B
1  a  f
2  b  g
3  c  h
4  d  i
5  e  j
```

For Series, only rows can be truncated.

```
>>> df['A'].truncate(before=2, after=4)
2    b
3    c
4    d
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={'A': 1})
>>> df.tail()
                     A
2016-01-31 23:59:56  1
2016-01-31 23:59:57  1
2016-01-31 23:59:58  1
2016-01-31 23:59:59  1
2016-02-01 00:00:00  1
```

```
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
...             after=pd.Timestamp('2016-01-10')).tail()
                     A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Because the index is a DatetimeIndex containing only dates, we can specify *before* and *after* as strings. They will be coerced to Timestamps before truncation.

```
>>> df.truncate('2016-01-05', '2016-01-10').tail()
                     A
2016-01-09 23:59:56  1
2016-01-09 23:59:57  1
2016-01-09 23:59:58  1
2016-01-09 23:59:59  1
2016-01-10 00:00:00  1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
                     A
2016-01-10 23:59:55  1
2016-01-10 23:59:56  1
2016-01-10 23:59:57  1
```

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```
2016-01-10 23:59:58  1
2016-01-10 23:59:59  1
```

pandas.DataFrame.tshift

DataFrame.**tshift**(*periods=1*, *freq=None*, *axis=0*)

Shift the time index, using the index's frequency if available.

Deprecated since version 1.1.0: Use *shift* instead.

Parameters

periods [int] Number of periods to move, can be positive or negative.

freq [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. 'EOM').

axis [{0 or 'index', 1 or 'columns', None}, default 0] Corresponds to the axis that contains the Index.

Returns

shifted [Series/DataFrame]

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

pandas.DataFrame.tz_convert

DataFrame.**tz_convert**(*tz*, *axis=0*, *level=None*, *copy=True*)

Convert tz-aware axis to target time zone.

Parameters

tz [str or tzinfo object]

axis [the axis to convert]

level [int, str, default None] If axis is a MultiIndex, convert a specific level. Otherwise must be None.

copy [bool, default True] Also make a copy of the underlying data.

Returns

{klass} Object with time zone converted axis.

Raises

TypeError If the axis is tz-naive.

pandas.DataFrame.tz_localize

DataFrame.**tz_localize**(*tz*, *axis=0*, *level=None*, *copy=True*, *ambiguous='raise'*, *nonexistent='raise'*)

Localize tz-naive index of a Series or DataFrame to target time zone.

This operation localizes the Index. To localize the values in a timezone-naive Series, use *Series.dt.tz_localize()*.

Parameters

tz [str or tzinfo]

axis [the axis to localize]

level [int, str, default None] If axis ia a MultiIndex, localize a specific level. Otherwise must be None.

copy [bool, default True] Also make a copy of the underlying data.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

nonexistent [str, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST. Valid values are:

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

Series or DataFrame Same type as the input.

Raises

TypeError If the TimeSeries is tz-aware and tz is not None.

Examples

Localize local times:

```
>>> s = pd.Series([1],
...               index=pd.DatetimeIndex(['2018-09-15 01:30:00']))
>>> s.tz_localize('CET')
2018-09-15 01:30:00+02:00    1
dtype: int64
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.Series(range(7),
...               index=pd.DatetimeIndex(['2018-10-28 01:30:00',
...                                       '2018-10-28 02:00:00',
...                                       '2018-10-28 02:30:00',
...                                       '2018-10-28 02:00:00',
...                                       '2018-10-28 02:30:00',
...                                       '2018-10-28 03:00:00',
...                                       '2018-10-28 03:30:00']))
>>> s.tz_localize('CET', ambiguous='infer')
2018-10-28 01:30:00+02:00    0
2018-10-28 02:00:00+02:00    1
2018-10-28 02:30:00+02:00    2
2018-10-28 02:00:00+01:00    3
2018-10-28 02:30:00+01:00    4
2018-10-28 03:00:00+01:00    5
2018-10-28 03:30:00+01:00    6
dtype: int64
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```
>>> s = pd.Series(range(3),
...               index=pd.DatetimeIndex(['2018-10-28 01:20:00',
...                                       '2018-10-28 02:36:00',
...                                       '2018-10-28 03:46:00']))
>>> s.tz_localize('CET', ambiguous=np.array([True, True, False]))
2018-10-28 01:20:00+02:00    0
2018-10-28 02:36:00+02:00    1
2018-10-28 03:46:00+01:00    2
dtype: int64
```

If the DST transition causes nonexistent times, you can shift these dates forward or backward with a timedelta object or *'shift_forward'* or *'shift_backward'*.

```
>>> s = pd.Series(range(2),
...               index=pd.DatetimeIndex(['2015-03-29 02:30:00',
...                                       '2015-03-29 03:30:00']))
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
2015-03-29 03:00:00+02:00    0
2015-03-29 03:30:00+02:00    1
dtype: int64
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
2015-03-29 01:59:59.999999999+01:00    0
2015-03-29 03:30:00+02:00              1
dtype: int64
>>> s.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
```

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```
2015-03-29 03:30:00+02:00    0
2015-03-29 03:30:00+02:00    1
dtype: int64
```

pandas.DataFrame.unstack

DataFrame.**unstack**(*level=-1*, *fill_value=None*)

Pivot a level of the (necessarily hierarchical) index labels.

Returns a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels.

If the index is not a MultiIndex, the output will be a Series (the analogue of stack when the columns are not a MultiIndex).

Parameters

level [int, str, or list of these, default -1 (last level)] Level(s) of index to unstack, can pass level name.

fill_value [int, str or dict] Replace NaN with this value if the unstack produces missing values.

Returns

Series or DataFrame

See also:

DataFrame.pivot Pivot a table based on column values.

DataFrame.stack Pivot a level of the column labels (inverse operation from *unstack*).

Examples

```
>>> index = pd.MultiIndex.from_tuples([('one', 'a'), ('one', 'b'),
...                                    ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one  a   1.0
     b   2.0
two  a   3.0
     b   4.0
dtype: float64
```

```
>>> s.unstack(level=-1)
     a   b
one  1.0  2.0
two  3.0  4.0
```

```
>>> s.unstack(level=0)
   one  two
a  1.0   3.0
b  2.0   4.0
```

```
>>> df = s.unstack(level=0)
>>> df.unstack()
one  a  1.0
     b  2.0
two  a  3.0
     b  4.0
dtype: float64
```

pandas.DataFrame.update

DataFrame.**update**(*other*, *join='left'*, *overwrite=True*, *filter_func=None*, *errors='ignore'*)

Modify in place using non-NA values from another DataFrame.

Aligns on indices. There is no return value.

Parameters

other [DataFrame, or object coercible into a DataFrame] Should have at least one matching index/column label with the original DataFrame. If a Series is passed, its name attribute must be set, and that will be used as the column name to align with the original DataFrame.

join [{'left'}, default 'left'] Only left join is implemented, keeping the index and columns of the original object.

overwrite [bool, default True] How to handle non-NA values for overlapping keys:

- True: overwrite original DataFrame's values with values from *other*.
- False: only update values that are NA in the original DataFrame.

filter_func [callable(1d-array) -> bool 1d-array, optional] Can choose to replace values other than NA. Return True for values that should be updated.

errors [{'raise', 'ignore'}, default 'ignore'] If 'raise', will raise a ValueError if the DataFrame and *other* both contain non-NA data in the same place.

Changed in version 0.24.0: Changed from *raise_conflict=False|True* to *errors='ignore'|'raise'*.

Returns

None [method directly changes calling object]

Raises

ValueError

- When *errors='raise'* and there's overlapping non-NA data.
- When *errors* is not either *'ignore'* or *'raise'*

NotImplementedError

- If *join != 'left'*

See also:

`dict.update` Similar method for dictionaries.

`DataFrame.merge` For column(s)-on-column(s) operations.

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3],
...                    'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, 5, 6],
...                        'C': [7, 8, 9]})
>>> df.update(new_df)
>>> df
   A  B
0  1  4
1  2  5
2  3  6
```

The DataFrame's length does not increase as a result of the update, only values at matching index/column labels are updated.

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
...                    'B': ['x', 'y', 'z']})
>>> new_df = pd.DataFrame({'B': ['d', 'e', 'f', 'g', 'h', 'i']})
>>> df.update(new_df)
>>> df
   A  B
0  a  d
1  b  e
2  c  f
```

For Series, its name attribute must be set.

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
...                    'B': ['x', 'y', 'z']})
>>> new_column = pd.Series(['d', 'e'], name='B', index=[0, 2])
>>> df.update(new_column)
>>> df
   A  B
0  a  d
1  b  y
2  c  e
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
...                    'B': ['x', 'y', 'z']})
>>> new_df = pd.DataFrame({'B': ['d', 'e']}, index=[1, 2])
>>> df.update(new_df)
>>> df
   A  B
0  a  x
1  b  d
2  c  e
```

If *other* contains NaNs the corresponding values are not updated in the original dataframe.

```
>>> df = pd.DataFrame({'A': [1, 2, 3],
...                    'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, np.nan, 6]})
>>> df.update(new_df)
>>> df
   A      B
0  1    4.0
1  2  500.0
2  3    6.0
```

pandas.DataFrame.value_counts

DataFrame.**value_counts**(*subset=None*, *normalize=False*, *sort=True*, *ascending=False*)

Return a Series containing counts of unique rows in the DataFrame.

New in version 1.1.0.

Parameters

subset [list-like, optional] Columns to use when counting unique combinations.

normalize [bool, default False] Return proportions rather than frequencies.

sort [bool, default True] Sort by frequencies.

ascending [bool, default False] Sort in ascending order.

Returns

Series

See also:

Series.value_counts Equivalent method on Series.

Notes

The returned Series will have a MultiIndex with one level per input column. By default, rows that contain any NA values are omitted from the result. By default, the resulting Series will be in descending order so that the first element is the most frequently-occurring row.

Examples

```
>>> df = pd.DataFrame({'num_legs': [2, 4, 4, 6],
...                    'num_wings': [2, 0, 0, 0]},
...                   index=['falcon', 'dog', 'cat', 'ant'])
>>> df
        num_legs  num_wings
falcon         2          2
dog            4          0
cat            4          0
ant            6          0
```

```
>>> df.value_counts()
num_legs  num_wings
4         0            2
2         2            1
6         0            1
dtype: int64
```

```
>>> df.value_counts(sort=False)
num_legs  num_wings
2         2            1
4         0            2
6         0            1
dtype: int64
```

```
>>> df.value_counts(ascending=True)
num_legs  num_wings
2         2            1
6         0            1
4         0            2
dtype: int64
```

```
>>> df.value_counts(normalize=True)
num_legs  num_wings
4         0            0.50
2         2            0.25
6         0            0.25
dtype: float64
```

pandas.DataFrame.var

DataFrame.**var**(*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis [{index (0), columns (1)}]

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

Series or DataFrame (if level specified)

Notes

To have the same behaviour as *numpy.std*, use *ddof=0* (instead of the default *ddof=1*)

pandas.DataFrame.where

DataFrame.**where**(*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *errors='raise'*, *try_cast=False*)

Replace values where the condition is False.

Parameters

cond [bool Series/DataFrame, array-like, or callable] Where *cond* is True, keep the original value. Where False, replace with corresponding value from *other*. If *cond* is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

other [scalar, Series/DataFrame, or callable] Entries where *cond* is False are replaced with corresponding value from *other*. If other is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

inplace [bool, default False] Whether to perform the operation in place on the data.

axis [int, default None] Alignment axis if needed.

level [int, default None] Alignment level if needed.

errors [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won't affect the results and will always coerce to a suitable dtype.

- 'raise' : allow exceptions to be raised.
- 'ignore' : suppress exceptions. On error return original object.

try_cast [bool, default False] Try to cast the result back to the input type (if possible).

Returns

Same type as caller or None if `inplace=True`.

See also:

`DataFrame.mask()` Return an object of same shape as self.

Notes

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if `cond` is `True` the element is used; otherwise the corresponding element from the DataFrame `other` is used.

The signature for *`DataFrame.where()`* differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the `where` documentation in *indexing*.

Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0
dtype: float64
>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0    10
1    10
2    2
3    3
4    4
dtype: int64
>>> s.mask(s > 1, 10)
0     0
1     1
2    10
3    10
4    10
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
4  8  9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0  0 -1
1 -2  3
2 -4 -5
3  6 -7
4 -8  9
>>> df.where(m, -df) == np.where(m, df, -df)
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
```

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```
      A     B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

pandas.DataFrame.xs

DataFrame.**xs**(*key*, *axis=0*, *level=None*, *drop_level=True*)

Return cross-section from the Series/DataFrame.

This method takes a *key* argument to select data at a particular level of a MultiIndex.

Parameters

key [label or tuple of label] Label contained in the index, or partially in a MultiIndex.

axis [{0 or 'index', 1 or 'columns'}, default 0] Axis to retrieve cross-section on.

level [object, defaults to first n levels (n=1 or len(key))] In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

drop_level [bool, default True] If False, returns object with same levels as self.

Returns

Series or DataFrame Cross-section from the original Series or DataFrame corresponding to the selected index levels.

See also:

DataFrame.loc Access a group of rows and columns by label(s) or a boolean array.

DataFrame.iloc Purely integer-location based indexing for selection by position.

Notes

xs can not be used to set values.

MultiIndex Slicers is a generic way to get/set values on any level or levels. It is a superset of *xs* functionality, see *MultiIndex Slicers*.

Examples

```
>>> d = {'num_legs': [4, 4, 2, 2],
...      'num_wings': [0, 0, 2, 2],
...      'class': ['mammal', 'mammal', 'mammal', 'bird'],
...      'animal': ['cat', 'dog', 'bat', 'penguin'],
...      'locomotion': ['walks', 'walks', 'flies', 'walks']}
>>> df = pd.DataFrame(data=d)
>>> df = df.set_index(['class', 'animal', 'locomotion'])
>>> df
                           num_legs  num_wings
```

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```
class  animal  locomotion
mammal cat     walks              4          0
       dog     walks              4          0
       bat     flies              2          2
bird   penguin walks              2          2
```

Get values at specified index

```
>>> df.xs('mammal')
                   num_legs  num_wings
animal locomotion
cat    walks              4          0
dog    walks              4          0
bat    flies              2          2
```

Get values at several indexes

```
>>> df.xs(('mammal', 'dog'))
            num_legs  num_wings
locomotion
walks              4          0
```

Get values at specified index and level

```
>>> df.xs('cat', level=1)
                   num_legs  num_wings
class  locomotion
mammal walks              4          0
```

Get values at several indexes and levels

```
>>> df.xs(('bird', 'walks'),
...        level=[0, 'locomotion'])
         num_legs  num_wings
animal
penguin         2          2
```

Get values at specified column and axis

```
>>> df.xs('num_wings', axis=1)
class   animal   locomotion
mammal  cat      walks         0
        dog      walks         0
        bat      flies         2
bird    penguin  walks         2
Name: num_wings, dtype: int64
```

3.4.2 Attributes and underlying data

Axes

DataFrame.index	The index (row labels) of the DataFrame.
DataFrame.columns	The column labels of the DataFrame.

DataFrame.dtypes	Return the dtypes in the DataFrame.
DataFrame.info([verbose, buf, max_cols, ...])	Print a concise summary of a DataFrame.
DataFrame.select_dtypes([include, exclude])	Return a subset of the DataFrame's columns based on the column dtypes.
DataFrame.values	Return a Numpy representation of the DataFrame.
DataFrame.axes	Return a list representing the axes of the DataFrame.
DataFrame.ndim	Return an int representing the number of axes / array dimensions.
DataFrame.size	Return an int representing the number of elements in this object.
DataFrame.shape	Return a tuple representing the dimensionality of the DataFrame.
DataFrame.memory_usage([index, deep])	Return the memory usage of each column in bytes.
DataFrame.empty	Indicator whether DataFrame is empty.
DataFrame.set_flags(*[, copy, ...])	Return a new object with updated flags.

3.4.3 Conversion

DataFrame.astype(dtype[, copy, errors])	Cast a pandas object to a specified dtype `dtype`.
DataFrame.convert_dtypes([infer_objects, ...])	Convert columns to best possible dtypes using dtypes supporting `pd.NA`.
DataFrame.infer_objects()	Attempt to infer better dtypes for object columns.
DataFrame.copy([deep])	Make a copy of this object's indices and data.
DataFrame.bool()	Return the bool of a single element Series or DataFrame.

3.4.4 Indexing, iteration

DataFrame.head([n])	Return the first *n* rows.
DataFrame.at	Access a single value for a row/column label pair.
DataFrame.iat	Access a single value for a row/column pair by integer position.
DataFrame.loc	Access a group of rows and columns by label(s) or a boolean array.
DataFrame.iloc	Purely integer-location based indexing for selection by position.
DataFrame.insert(loc, column, value[, ...])	Insert column into DataFrame at specified location.
DataFrame.__iter__()	Iterate over info axis.
DataFrame.items()	Iterate over (column name, Series) pairs.
DataFrame.iteritems()	Iterate over (column name, Series) pairs.

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DataFrame.keys()	Get the 'info axis' (see Indexing for more).
DataFrame.iterrows()	Iterate over DataFrame rows as (index, Series) pairs.
DataFrame.itertuples([index, name])	Iterate over DataFrame rows as namedtuples.
DataFrame.lookup(row_labels, col_labels)	(DEPRECATED) Label-based "fancy indexing" function for DataFrame.
DataFrame.pop(item)	Return item and drop from frame.
DataFrame.tail([n])	Return the last *n* rows.
DataFrame.xs(key[, axis, level, drop_level])	Return cross-section from the Series/DataFrame.
DataFrame.get(key[, default])	Get item from object for given key (ex: DataFrame column).
DataFrame.isin(values)	Whether each element in the DataFrame is contained in values.
DataFrame.where(cond[, other, inplace, ...])	Replace values where the condition is False.
DataFrame.mask(cond[, other, inplace, axis, ...])	Replace values where the condition is True.
DataFrame.query(expr[, inplace])	Query the columns of a DataFrame with a boolean expression.

pandas.DataFrame.__iter__

DataFrame.__iter__()

Iterate over info axis.

Returns

iterator Info axis as iterator.

For more information on `.at`, `.iat`, `.loc`, and `.iloc`, see the *indexing documentation*.

3.4.5 Binary operator functions

DataFrame.add(other[, axis, level, fill_value])	Get Addition of dataframe and other, element-wise (binary operator *add*).
DataFrame.sub(other[, axis, level, fill_value])	Get Subtraction of dataframe and other, element-wise (binary operator *sub*).
DataFrame.mul(other[, axis, level, fill_value])	Get Multiplication of dataframe and other, element-wise (binary operator *mul*).
DataFrame.div(other[, axis, level, fill_value])	Get Floating division of dataframe and other, element-wise (binary operator *truediv*).
DataFrame.truediv(other[, axis, level, ...])	Get Floating division of dataframe and other, element-wise (binary operator *truediv*).
DataFrame.floordiv(other[, axis, level, ...])	Get Integer division of dataframe and other, element-wise (binary operator *floordiv*).
DataFrame.mod(other[, axis, level, fill_value])	Get Modulo of dataframe and other, element-wise (binary operator *mod*).
DataFrame.pow(other[, axis, level, fill_value])	Get Exponential power of dataframe and other, element-wise (binary operator *pow*).
DataFrame.dot(other)	Compute the matrix multiplication between the DataFrame and other.
DataFrame.radd(other[, axis, level, fill_value])	Get Addition of dataframe and other, element-wise (binary operator *radd*).

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Table 65 – continued from previous page

DataFrame.rsub(other[, axis, level, fill_value])	Get Subtraction of dataframe and other, element-wise (binary operator *rsub*).
DataFrame.rmul(other[, axis, level, fill_value])	Get Multiplication of dataframe and other, element-wise (binary operator *rmul*).
DataFrame.rdiv(other[, axis, level, fill_value])	Get Floating division of dataframe and other, element-wise (binary operator *rtruediv*).
DataFrame.rtruediv(other[, axis, level, ...])	Get Floating division of dataframe and other, element-wise (binary operator *rtruediv*).
DataFrame.rfloordiv(other[, axis, level, ...])	Get Integer division of dataframe and other, element-wise (binary operator *rfloordiv*).
DataFrame.rmod(other[, axis, level, fill_value])	Get Modulo of dataframe and other, element-wise (binary operator *rmod*).
DataFrame.rpow(other[, axis, level, fill_value])	Get Exponential power of dataframe and other, element-wise (binary operator *rpow*).
DataFrame.lt(other[, axis, level])	Get Less than of dataframe and other, element-wise (binary operator *lt*).
DataFrame.gt(other[, axis, level])	Get Greater than of dataframe and other, element-wise (binary operator *gt*).
DataFrame.le(other[, axis, level])	Get Less than or equal to of dataframe and other, element-wise (binary operator *le*).
DataFrame.ge(other[, axis, level])	Get Greater than or equal to of dataframe and other, element-wise (binary operator *ge*).
DataFrame.ne(other[, axis, level])	Get Not equal to of dataframe and other, element-wise (binary operator *ne*).
DataFrame.eq(other[, axis, level])	Get Equal to of dataframe and other, element-wise (binary operator *eq*).
DataFrame.combine(other, func[, fill_value, ...])	Perform column-wise combine with another DataFrame.
DataFrame.combine_first(other)	Update null elements with value in the same location in *other*.

3.4.6 Function application, GroupBy & window

DataFrame.apply(func[, axis, raw, ...])	Apply a function along an axis of the DataFrame.
DataFrame.applymap(func[, na_action])	Apply a function to a Dataframe elementwise.
DataFrame.pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs).
DataFrame.agg([func, axis])	Aggregate using one or more operations over the specified axis.
DataFrame.aggregate([func, axis])	Aggregate using one or more operations over the specified axis.
DataFrame.transform(func[, axis])	Call `func` on self producing a DataFrame with transformed values.
DataFrame.groupby([by, axis, level, ...])	Group DataFrame using a mapper or by a Series of columns.
DataFrame.rolling(window[, min_periods, ...])	Provide rolling window calculations.
DataFrame.expanding([min_periods, center, axis])	Provide expanding transformations.
DataFrame.ewm([com, span, halflife, alpha, ...])	Provide exponential weighted (EW) functions.

3.4.7 Computations / descriptive stats

DataFrame.abs()	Return a Series/DataFrame with absolute numeric value of each element.
DataFrame.all([axis, bool_only, skipna, level])	Return whether all elements are True, potentially over an axis.
DataFrame.any([axis, bool_only, skipna, level])	Return whether any element is True, potentially over an axis.
DataFrame.clip([lower, upper, axis, inplace])	Trim values at input threshold(s).
DataFrame.corr([method, min_periods])	Compute pairwise correlation of columns, excluding NA/null values.
DataFrame.corrwith(other[, axis, drop, method])	Compute pairwise correlation.
DataFrame.count([axis, level, numeric_only])	Count non-NA cells for each column or row.
DataFrame.cov([min_periods, ddof])	Compute pairwise covariance of columns, excluding NA/null values.
DataFrame.cummax([axis, skipna])	Return cumulative maximum over a DataFrame or Series axis.
DataFrame.cummin([axis, skipna])	Return cumulative minimum over a DataFrame or Series axis.
DataFrame.cumprod([axis, skipna])	Return cumulative product over a DataFrame or Series axis.
DataFrame.cumsum([axis, skipna])	Return cumulative sum over a DataFrame or Series axis.
DataFrame.describe([percentiles, include, ...])	Generate descriptive statistics.
DataFrame.diff([periods, axis])	First discrete difference of element.
DataFrame.eval(expr[, inplace])	Evaluate a string describing operations on DataFrame columns.
DataFrame.kurt([axis, skipna, level, ...])	Return unbiased kurtosis over requested axis.
DataFrame.kurtosis([axis, skipna, level, ...])	Return unbiased kurtosis over requested axis.
DataFrame.mad([axis, skipna, level])	Return the mean absolute deviation of the values over the requested axis.
DataFrame.max([axis, skipna, level, ...])	Return the maximum of the values over the requested axis.
DataFrame.mean([axis, skipna, level, ...])	Return the mean of the values over the requested axis.
DataFrame.median([axis, skipna, level, ...])	Return the median of the values over the requested axis.
DataFrame.min([axis, skipna, level, ...])	Return the minimum of the values over the requested axis.
DataFrame.mode([axis, numeric_only, dropna])	Get the mode(s) of each element along the selected axis.
DataFrame.pct_change([periods, fill_method, ...])	Percentage change between the current and a prior element.
DataFrame.prod([axis, skipna, level, ...])	Return the product of the values over the requested axis.
DataFrame.product([axis, skipna, level, ...])	Return the product of the values over the requested axis.
DataFrame.quantile([q, axis, numeric_only, ...])	Return values at the given quantile over requested axis.
DataFrame.rank([axis, method, numeric_only, ...])	Compute numerical data ranks (1 through n) along axis.
DataFrame.round([decimals])	Round a DataFrame to a variable number of decimal places.
DataFrame.sem([axis, skipna, level, ddof, ...])	Return unbiased standard error of the mean over requested axis.
DataFrame.skew([axis, skipna, level, ...])	Return unbiased skew over requested axis.
DataFrame.sum([axis, skipna, level, ...])	Return the sum of the values over the requested axis.

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Table 67 – continued from previous page

DataFrame.std([axis, skipna, level, ddof, ...])	Return sample standard deviation over requested axis.
DataFrame.var([axis, skipna, level, ddof, ...])	Return unbiased variance over requested axis.
DataFrame.nunique([axis, dropna])	Count distinct observations over requested axis.
DataFrame.value_counts([subset, normalize, ...])	Return a Series containing counts of unique rows in the DataFrame.

3.4.8 Reindexing / selection / label manipulation

DataFrame.add_prefix(prefix)	Prefix labels with string *prefix*.
DataFrame.add_suffix(suffix)	Suffix labels with string *suffix*.
DataFrame.align(other[, join, axis, level, ...])	Align two objects on their axes with the specified join method.
DataFrame.at_time(time[, asof, axis])	Select values at particular time of day (e.g., 9:30AM).
DataFrame.between_time(start_time, end_time)	Select values between particular times of the day (e.g., 9:00-9:30 AM).
DataFrame.drop([labels, axis, index, ...])	Drop specified labels from rows or columns.
DataFrame.drop_duplicates([subset, keep, ...])	Return DataFrame with duplicate rows removed.
DataFrame.duplicated([subset, keep])	Return boolean Series denoting duplicate rows.
DataFrame.equals(other)	Test whether two objects contain the same elements.
DataFrame.filter([items, like, regex, axis])	Subset the dataframe rows or columns according to the specified index labels.
DataFrame.first(offset)	Select initial periods of time series data based on a date offset.
DataFrame.head([n])	Return the first *n* rows.
DataFrame.idxmax([axis, skipna])	Return index of first occurrence of maximum over requested axis.
DataFrame.idxmin([axis, skipna])	Return index of first occurrence of minimum over requested axis.
DataFrame.last(offset)	Select final periods of time series data based on a date offset.
DataFrame.reindex([labels, index, columns, ...])	Conform Series/DataFrame to new index with optional filling logic.
DataFrame.reindex_like(other[, method, ...])	Return an object with matching indices as other object.
DataFrame.rename([mapper, index, columns, ...])	Alter axes labels.
DataFrame.rename_axis([mapper, index, ...])	Set the name of the axis for the index or columns.
DataFrame.reset_index([level, drop, ...])	Reset the index, or a level of it.
DataFrame.sample([n, frac, replace, ...])	Return a random sample of items from an axis of object.
DataFrame.set_axis(labels[, axis, inplace])	Assign desired index to given axis.
DataFrame.set_index(keys[, drop, append, ...])	Set the DataFrame index using existing columns.
DataFrame.tail([n])	Return the last *n* rows.
DataFrame.take(indices[, axis, is_copy])	Return the elements in the given *positional* indices along an axis.
DataFrame.truncate([before, after, axis, copy])	Truncate a Series or DataFrame before and after some index value.

3.4.9 Missing data handling

DataFrame.backfill([axis, inplace, limit, ...])	Synonym for DataFrame.fillna() with method='bfill'.
DataFrame.bfill([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='bfill'.
DataFrame.dropna([axis, how, thresh, ...])	Remove missing values.
DataFrame.ffill([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='ffill'.
DataFrame.fillna([value, method, axis, ...])	Fill NA/NaN values using the specified method.
DataFrame.interpolate([method, axis, limit, ...])	Fill NaN values using an interpolation method.
DataFrame.isna()	Detect missing values.
DataFrame.isnull()	Detect missing values.
DataFrame.notna()	Detect existing (non-missing) values.
DataFrame.notnull()	Detect existing (non-missing) values.
DataFrame.pad([axis, inplace, limit, downcast])	Synonym for DataFrame.fillna() with method='ffill'.
DataFrame.replace([to_replace, value, ...])	Replace values given in *to_replace* with *value*.

3.4.10 Reshaping, sorting, transposing

DataFrame.droplevel(level[, axis])	Return DataFrame with requested index / column level(s) removed.
DataFrame.pivot([index, columns, values])	Return reshaped DataFrame organized by given index / column values.
DataFrame.pivot_table([values, index, ...])	Create a spreadsheet-style pivot table as a DataFrame.
DataFrame.reorder_levels(order[, axis])	Rearrange index levels using input order.
DataFrame.sort_values(by[, axis, ascending, ...])	Sort by the values along either axis.
DataFrame.sort_index([axis, level, ...])	Sort object by labels (along an axis).
DataFrame.nlargest(n, columns[, keep])	Return the first *n* rows ordered by *columns* in descending order.
DataFrame.nsmallest(n, columns[, keep])	Return the first *n* rows ordered by *columns* in ascending order.
DataFrame.swaplevel([i, j, axis])	Swap levels i and j in a MultiIndex on a particular axis.
DataFrame.stack([level, dropna])	Stack the prescribed level(s) from columns to index.
DataFrame.unstack([level, fill_value])	Pivot a level of the (necessarily hierarchical) index labels.
DataFrame.swapaxes(axis1, axis2[, copy])	Interchange axes and swap values axes appropriately.
DataFrame.melt([id_vars, value_vars, ...])	Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.
DataFrame.explode(column[, ignore_index])	Transform each element of a list-like to a row, replicating index values.
DataFrame.squeeze([axis])	Squeeze 1 dimensional axis objects into scalars.
DataFrame.to_xarray()	Return an xarray object from the pandas object.
DataFrame.T	
DataFrame.transpose(*args[, copy])	Transpose index and columns.

pandas.DataFrame.T

property DataFrame.**T**

3.4.11 Combining / comparing / joining / merging

DataFrame.append(other[, ignore_index, ...])	Append rows of *other* to the end of caller, returning a new object.
DataFrame.assign(**kwargs)	Assign new columns to a DataFrame.
DataFrame.compare(other[, align_axis, ...])	Compare to another DataFrame and show the differences.
DataFrame.join(other[, on, how, lsuffix, ...])	Join columns of another DataFrame.
DataFrame.merge(right[, how, on, left_on, ...])	Merge DataFrame or named Series objects with a database-style join.
DataFrame.update(other[, join, overwrite, ...])	Modify in place using non-NA values from another DataFrame.

3.4.12 Time Series-related

DataFrame.asfreq(freq[, method, how, ...])	Convert TimeSeries to specified frequency.
DataFrame.asof(where[, subset])	Return the last row(s) without any NaNs before *where*.
DataFrame.shift([periods, freq, axis, ...])	Shift index by desired number of periods with an optional time *freq*.
DataFrame.slice_shift([periods, axis])	(DEPRECATED) Equivalent to *shift* without copying data.
DataFrame.tshift([periods, freq, axis])	(DEPRECATED) Shift the time index, using the index's frequency if available.
DataFrame.first_valid_index()	Return index for first non-NA/null value.
DataFrame.last_valid_index()	Return index for last non-NA/null value.
DataFrame.resample(rule[, axis, closed, ...])	Resample time-series data.
DataFrame.to_period([freq, axis, copy])	Convert DataFrame from DatetimeIndex to PeriodIndex.
DataFrame.to_timestamp([freq, how, axis, copy])	Cast to DatetimeIndex of timestamps, at *beginning* of period.
DataFrame.tz_convert(tz[, axis, level, copy])	Convert tz-aware axis to target time zone.
DataFrame.tz_localize(tz[, axis, level, ...])	Localize tz-naive index of a Series or DataFrame to target time zone.

3.4.13 Flags

Flags refer to attributes of the pandas object. Properties of the dataset (like the date is was recorded, the URL it was accessed from, etc.) should be stored in DataFrame.attrs.

Flags(obj, *, allows_duplicate_labels)	Flags that apply to pandas objects.

3.4.14 Metadata

DataFrame.attrs is a dictionary for storing global metadata for this DataFrame.

Warning: `DataFrame.attrs` is considered experimental and may change without warning.

DataFrame.attrs	Dictionary of global attributes of this dataset.

3.4.15 Plotting

`DataFrame.plot` is both a callable method and a namespace attribute for specific plotting methods of the form `DataFrame.plot.<kind>`.

DataFrame.plot([x, y, kind, ax, ...])	DataFrame plotting accessor and method

DataFrame.plot.area([x, y])	Draw a stacked area plot.
DataFrame.plot.bar([x, y])	Vertical bar plot.
DataFrame.plot.barh([x, y])	Make a horizontal bar plot.
DataFrame.plot.box([by])	Make a box plot of the DataFrame columns.
DataFrame.plot.density([bw_method, ind])	Generate Kernel Density Estimate plot using Gaussian kernels.
DataFrame.plot.hexbin(x, y[, C, ...])	Generate a hexagonal binning plot.
DataFrame.plot.hist([by, bins])	Draw one histogram of the DataFrame's columns.
DataFrame.plot.kde([bw_method, ind])	Generate Kernel Density Estimate plot using Gaussian kernels.
DataFrame.plot.line([x, y])	Plot Series or DataFrame as lines.
DataFrame.plot.pie(**kwargs)	Generate a pie plot.
DataFrame.plot.scatter(x, y[, s, c])	Create a scatter plot with varying marker point size and color.

pandas.DataFrame.plot.area

`DataFrame.plot.`**`area`**(*x=None*, *y=None*, ***kwargs*)

Draw a stacked area plot.

An area plot displays quantitative data visually. This function wraps the matplotlib area function.

Parameters

x [label or position, optional] Coordinates for the X axis. By default uses the index.

y [label or position, optional] Column to plot. By default uses all columns.

stacked [bool, default True] Area plots are stacked by default. Set to False to create a unstacked plot.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or numpy.ndarray Area plot, or array of area plots if subplots is True.

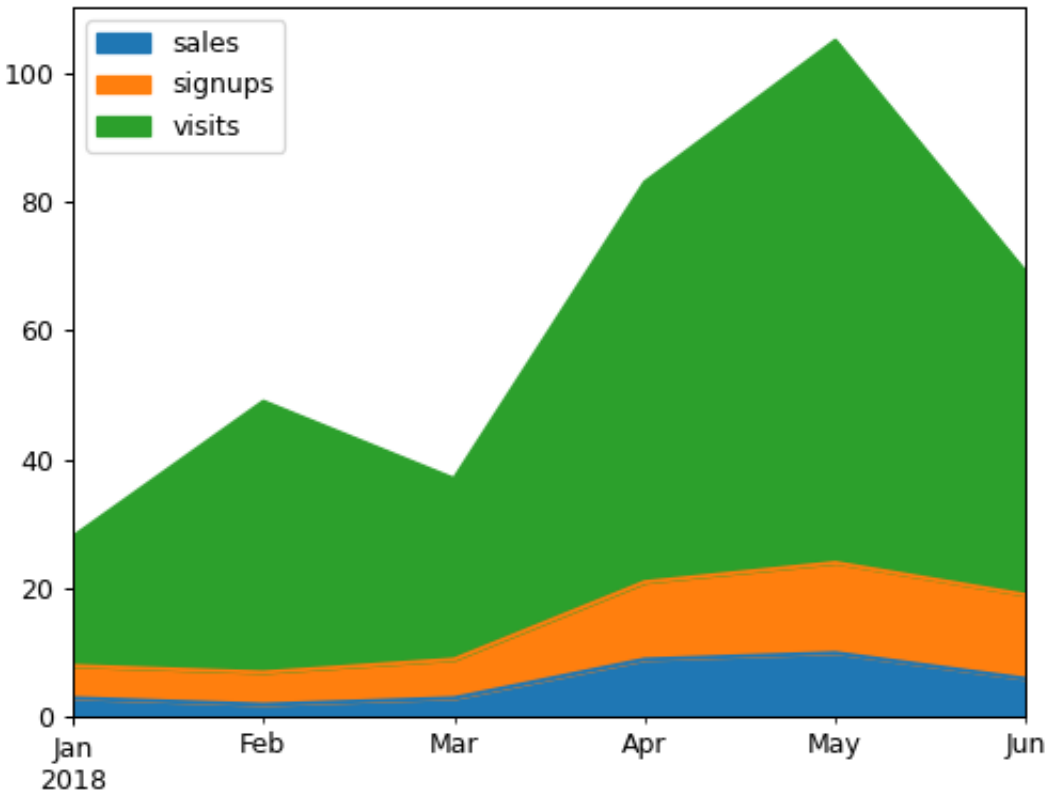
See also:

DataFrame.plot Make plots of DataFrame using matplotlib / pylab.

Examples

Draw an area plot based on basic business metrics:

```
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3, 9, 10, 6],
...     'signups': [5, 5, 6, 12, 14, 13],
...     'visits': [20, 42, 28, 62, 81, 50],
... }, index=pd.date_range(start='2018/01/01', end='2018/07/01',
...                        freq='M'))
>>> ax = df.plot.area()
```



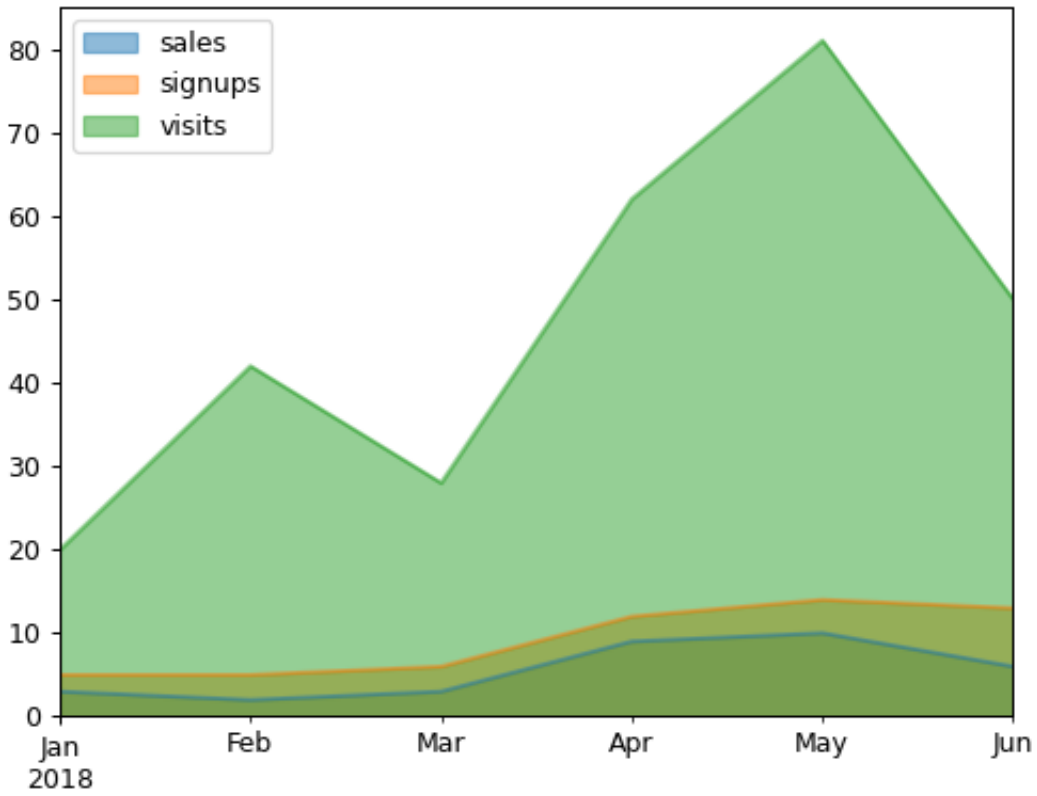
Area plots are stacked by default. To produce an unstacked plot, pass `stacked=False`:

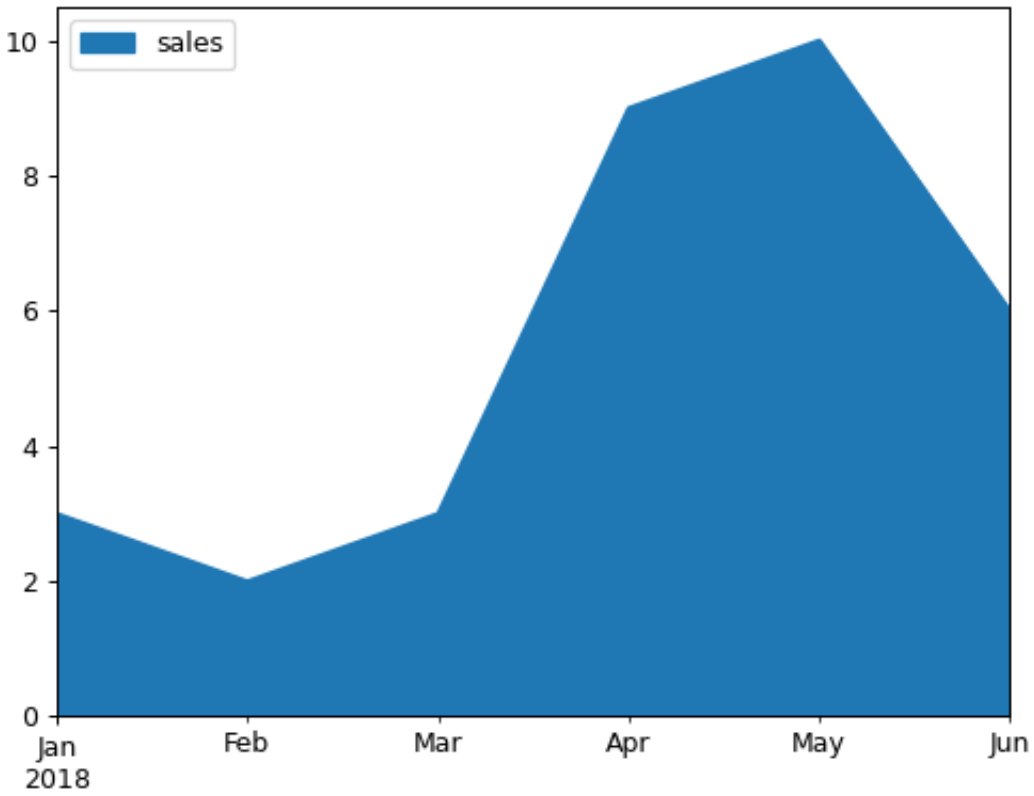
```
>>> ax = df.plot.area(stacked=False)
```

Draw an area plot for a single column:

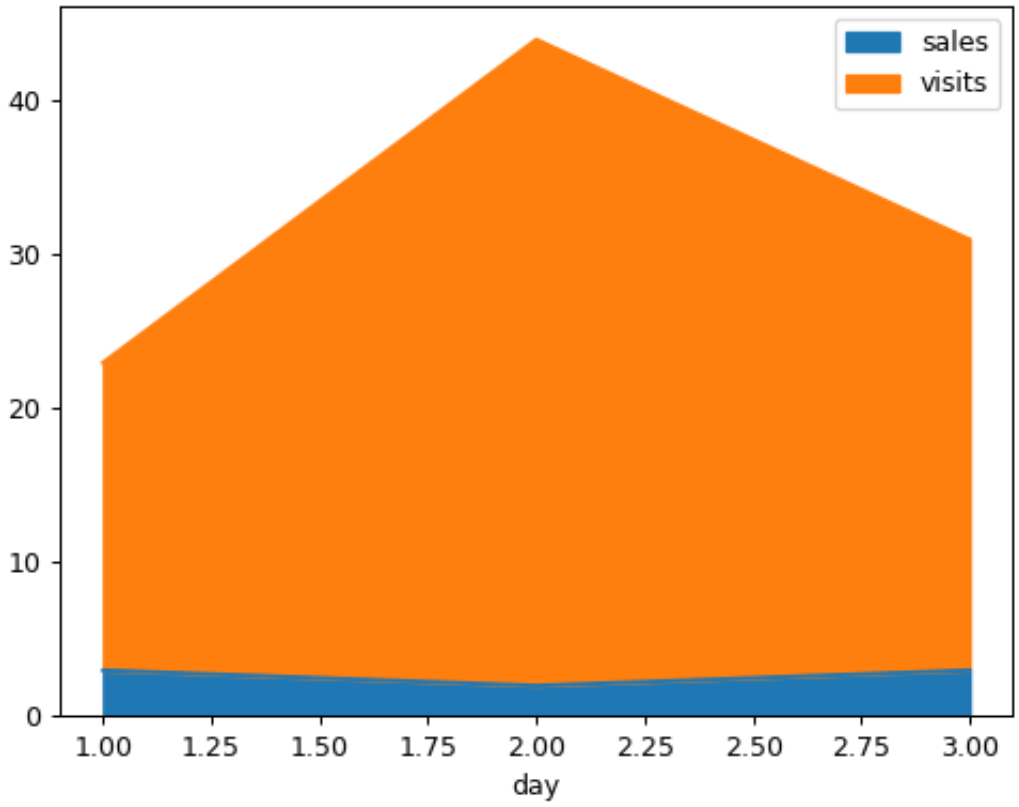
```
>>> ax = df.plot.area(y='sales')
```

Draw with a different *x*:


sales
signups
visits
80
70
60
50
40
30
20
10
0
Jan
2018
Feb
Mar
Apr
May
Jun


sales
10
8
6
4
2
0
Jan
2018
Feb
Mar
Apr
May
Jun

```
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3],
...     'visits': [20, 42, 28],
...     'day': [1, 2, 3],
... })
>>> ax = df.plot.area(x='day')
```



pandas.DataFrame.plot.bar

`DataFrame.plot.`**`bar`**(*x=None*, *y=None*, ***kwargs*)

Vertical bar plot.

A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

Parameters

x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

color [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:

- **A single color string referred to by name, RGB or RGBA code,** for instance 'red' or '#a98d19'.
- **A sequence of color strings referred to by name, RGB or RGBA** code, which will be used for each column recursively. For instance ['green','yellow'] each column's bar will be filled in green or yellow, alternatively.
- **A dict of the form {column name** [color}, so that each column will be] colored accordingly. For example, if your columns are called *a* and *b*, then passing {'a': 'green', 'b': 'red'} will color bars for column *a* in green and bars for column *b* in red.

New in version 1.1.0.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

See also:

DataFrame.plot.barh Horizontal bar plot.
DataFrame.plot Make plots of a DataFrame.
matplotlib.pyplot.bar Make a bar plot with matplotlib.

Examples

Basic plot.

```
>>> df = pd.DataFrame({'lab':['A', 'B', 'C'], 'val':[10, 30, 20]})
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```

Plot a whole dataframe to a bar plot. Each column is assigned a distinct color, and each row is nested in a group along the horizontal axis.

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.bar(rot=0)
```

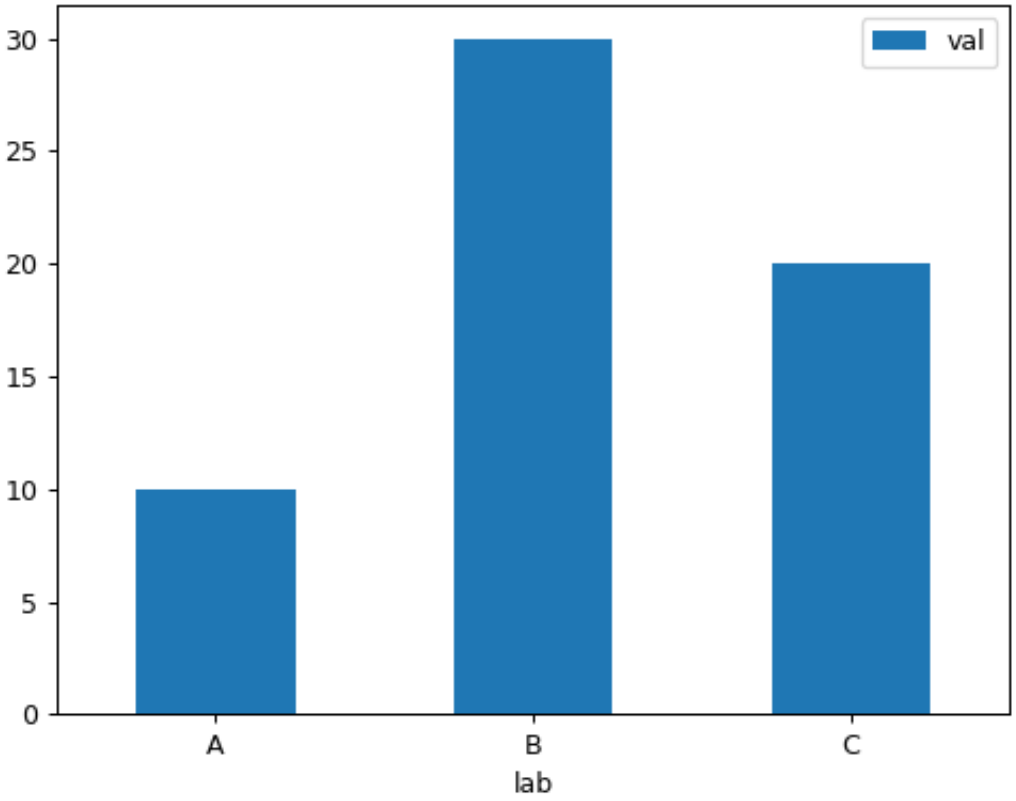
Plot stacked bar charts for the DataFrame

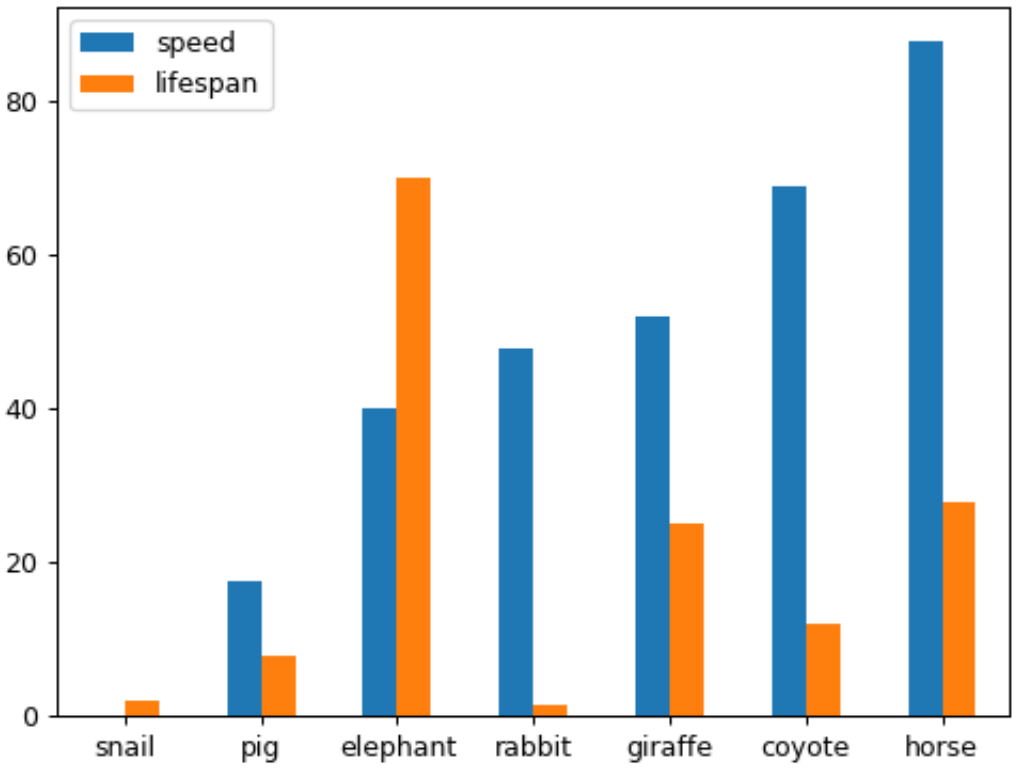
```
>>> ax = df.plot.bar(stacked=True)
```

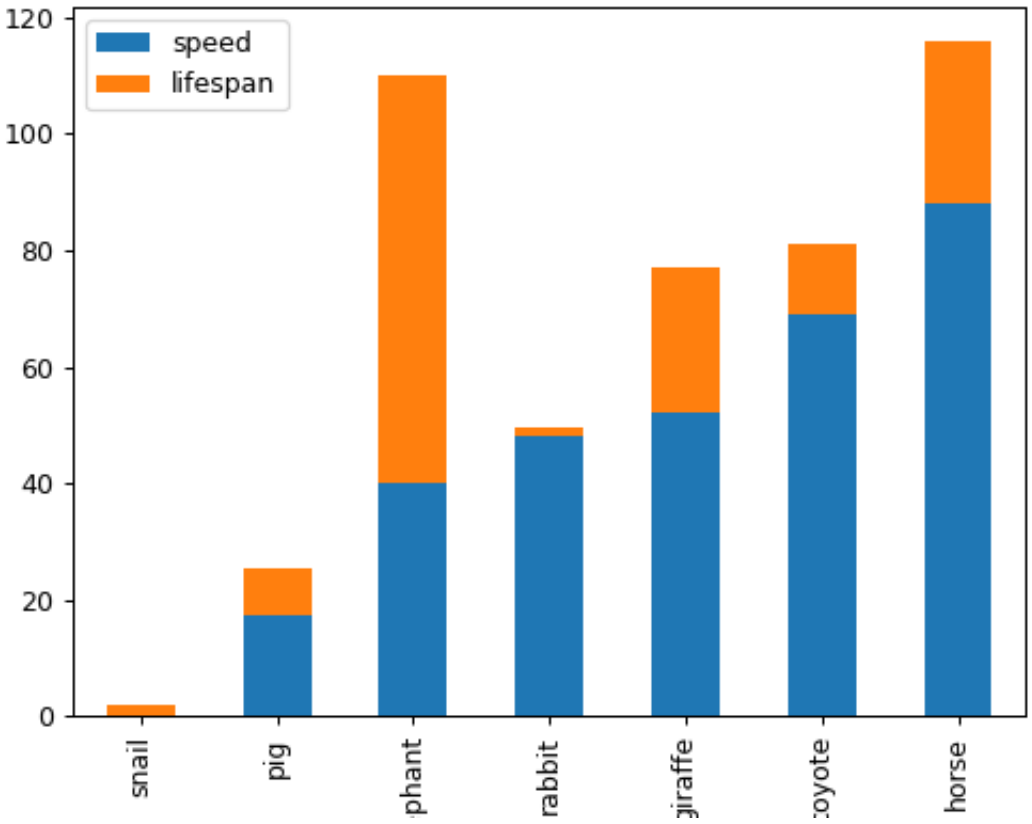
Instead of nesting, the figure can be split by column with `subplots=True`. In this case, a `numpy.ndarray` of `matplotlib.axes.Axes` are returned.

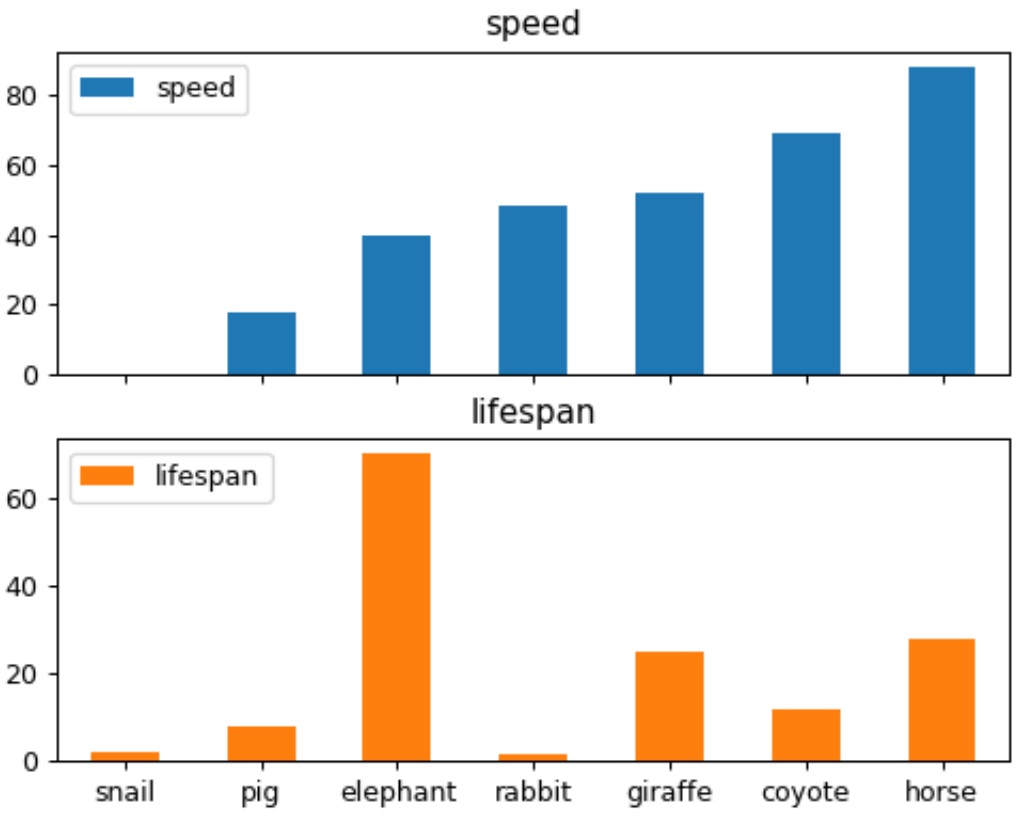
```
>>> axes = df.plot.bar(rot=0, subplots=True)
>>> axes[1].legend(loc=2)
```

If you don't like the default colours, you can specify how you'd like each column to be colored.

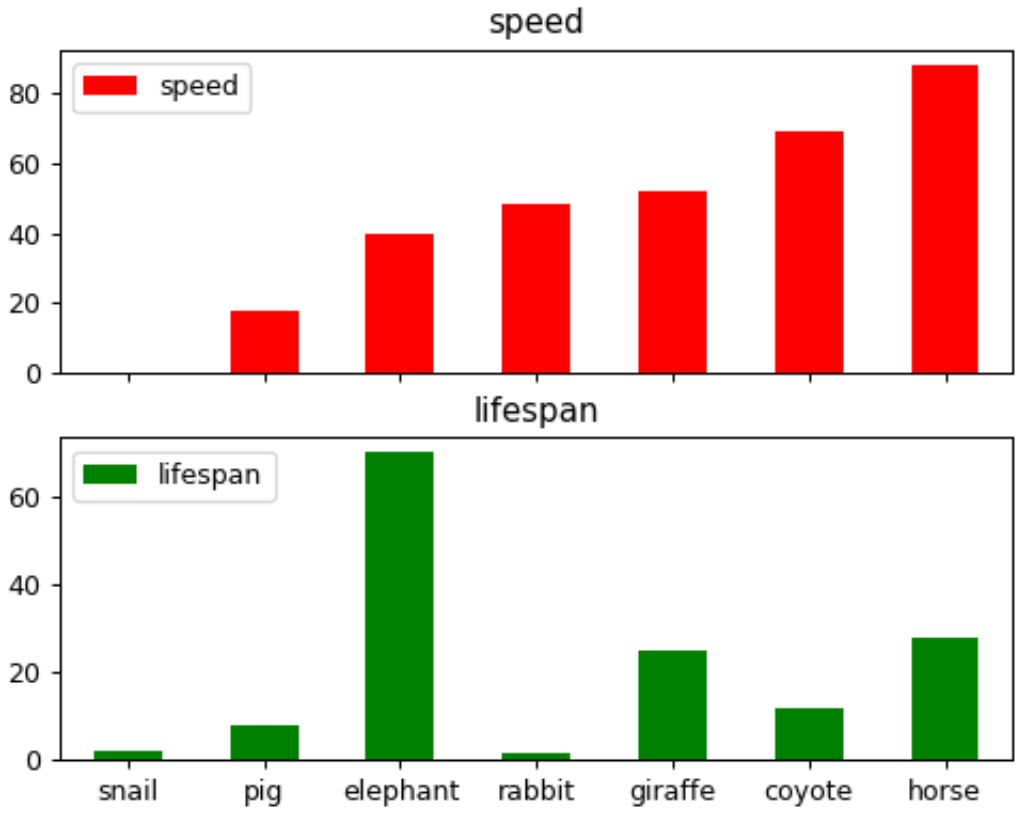

val
30
25
20
15
10
5
0
A
B
C
lab


speed
lifespan
80
60
40
20
0
snail
pig
elephant
rabbit
giraffe
coyote
horse


speed
lifespan
120
100
80
60
40
20
0
snail
pig
phant
rabbit
giraffe
coyote
horse


speed
speed
80
60
40
20
0
lifespan
lifespan
60
40
20
0
snail
pig
elephant
rabbit
giraffe
coyote
horse

```
>>> axes = df.plot.bar(
...     rot=0, subplots=True, color={"speed": "red", "lifespan": "green"}
... )
>>> axes[1].legend(loc=2)
```



Plot a single column.

```
>>> ax = df.plot.bar(y='speed', rot=0)
```

Plot only selected categories for the DataFrame.

```
>>> ax = df.plot.bar(x='lifespan', rot=0)
```

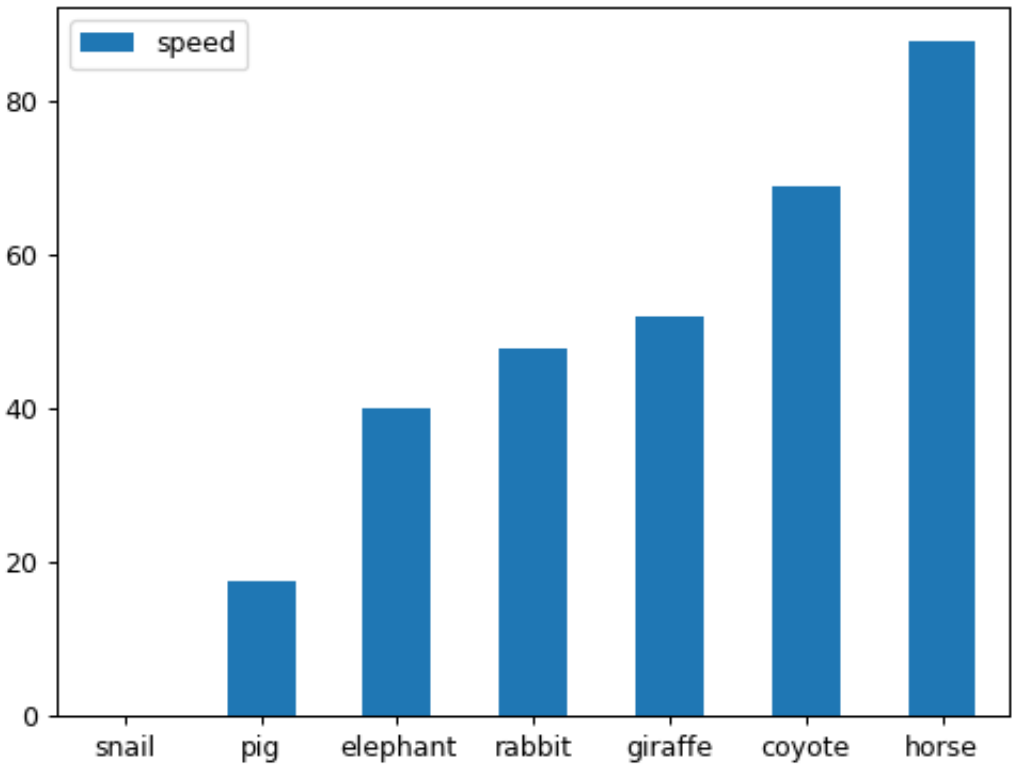
pandas.DataFrame.plot.barh

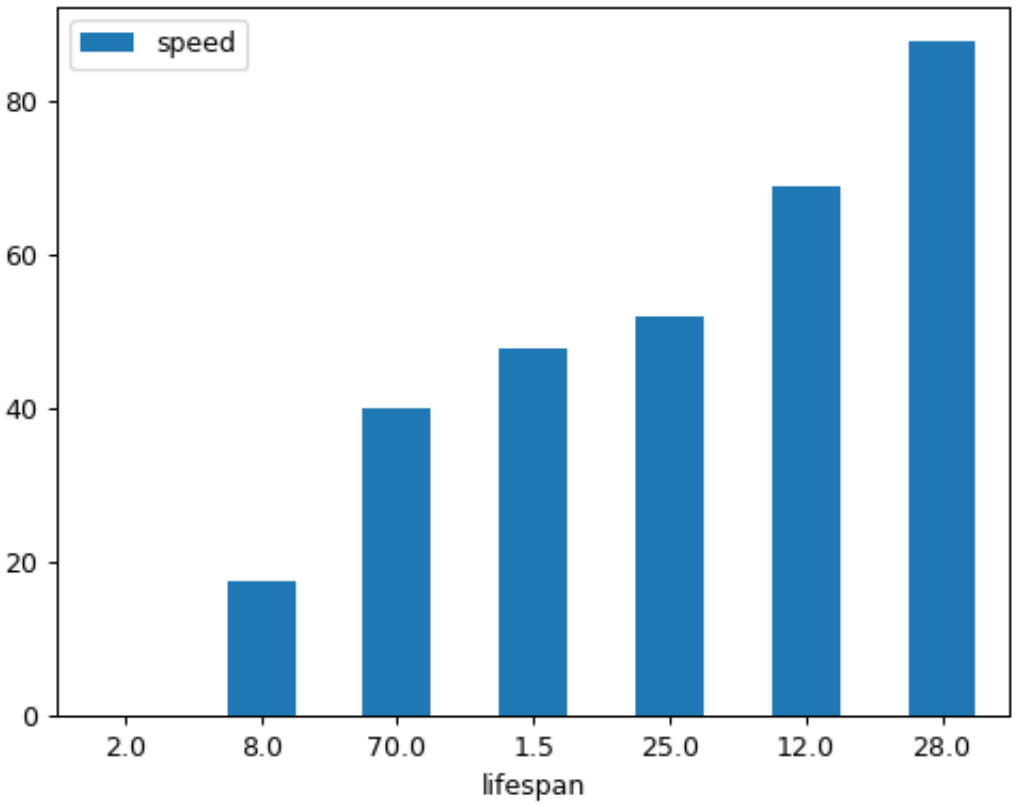
`DataFrame.plot.`**`barh`**(*x=None*, *y=None*, ***kwargs*)

Make a horizontal bar plot.

A horizontal bar plot is a plot that presents quantitative data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

Parameters


speed
80
60
40
20
0
snail
pig
elephant
rabbit
giraffe
coyote
horse


speed
80
60
40
20
0
2.0
8.0
70.0
1.5
25.0
12.0
28.0
lifespan

x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

color [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:

- **A single color string referred to by name, RGB or RGBA code,** for instance 'red' or '#a98d19'.
- **A sequence of color strings referred to by name, RGB or RGBA** code, which will be used for each column recursively. For instance ['green','yellow'] each column's bar will be filled in green or yellow, alternatively.
- **A dict of the form {column name** [color}, so that each column will be] colored accordingly. For example, if your columns are called *a* and *b*, then passing {'a': 'green', 'b': 'red'} will color bars for column *a* in green and bars for column *b* in red.

New in version 1.1.0.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

See also:

DataFrame.plot.bar Vertical bar plot.
DataFrame.plot Make plots of DataFrame using matplotlib.
matplotlib.axes.Axes.bar Plot a vertical bar plot using matplotlib.

Examples

Basic example

```
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})
>>> ax = df.plot.barh(x='lab', y='val')
```

Plot a whole DataFrame to a horizontal bar plot

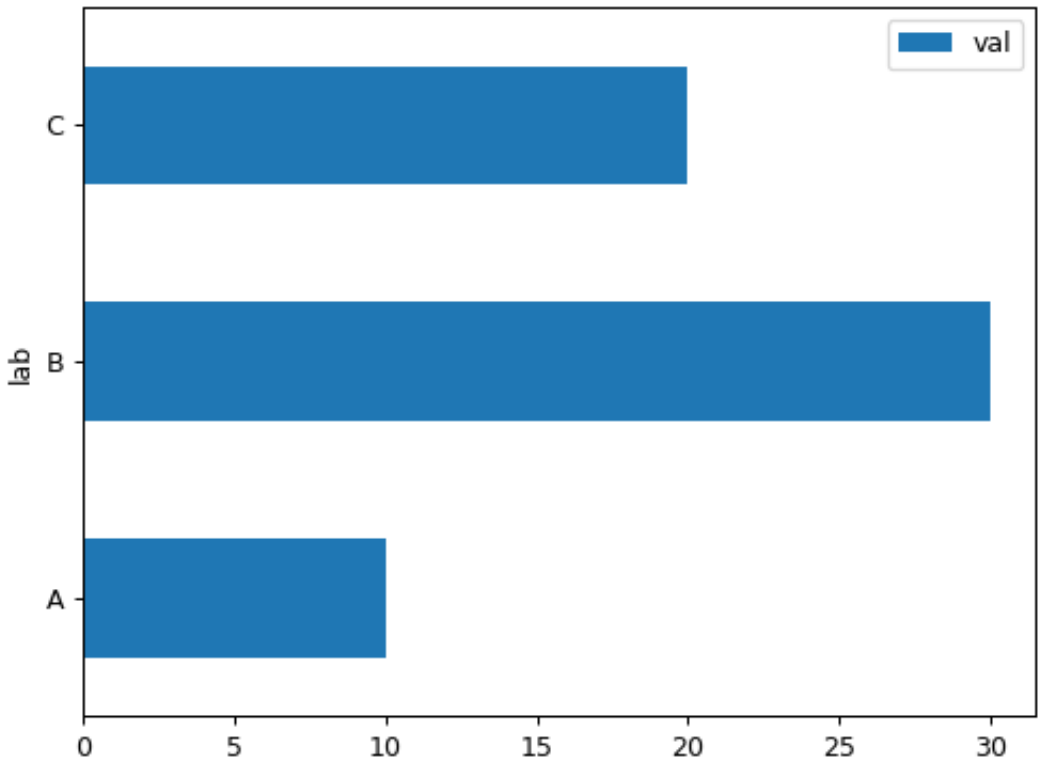
```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh()
```

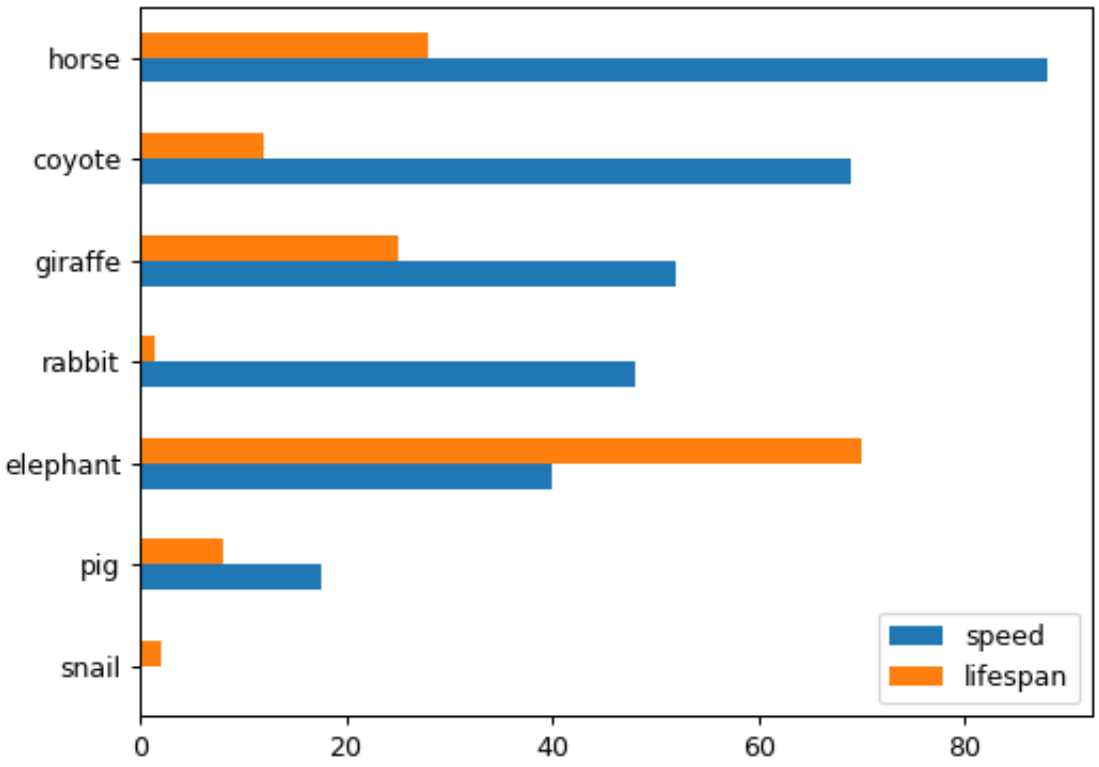
Plot stacked barh charts for the DataFrame

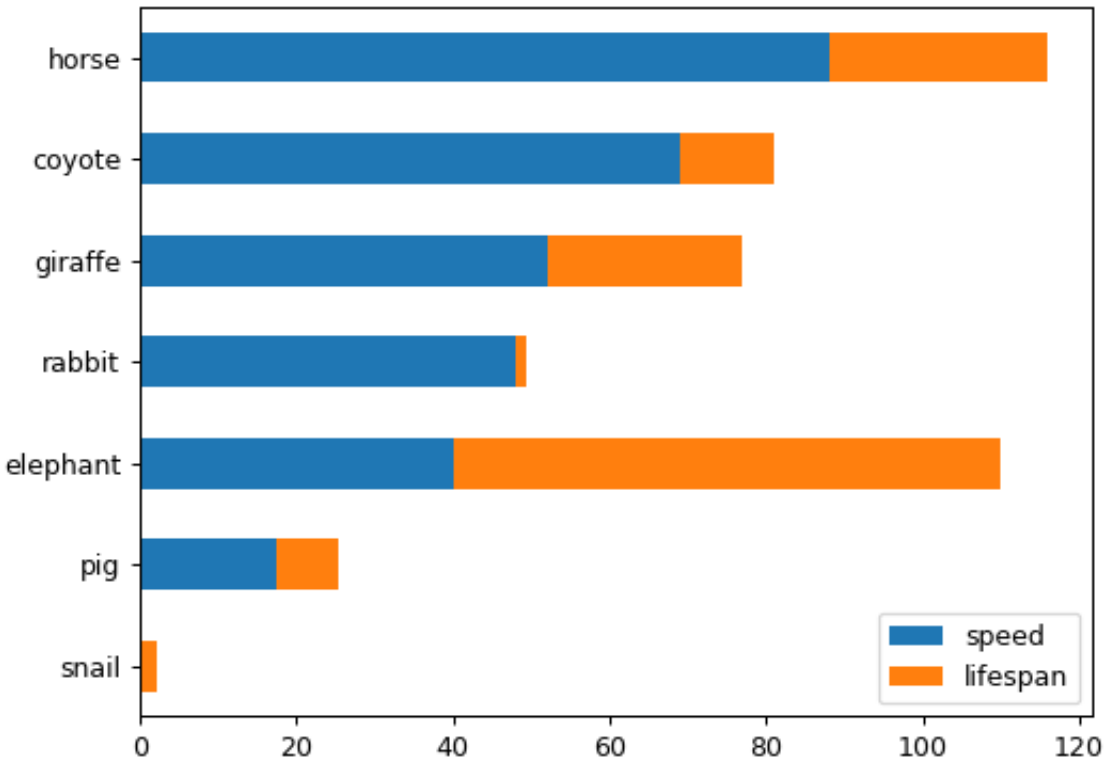
```
>>> ax = df.plot.barh(stacked=True)
```

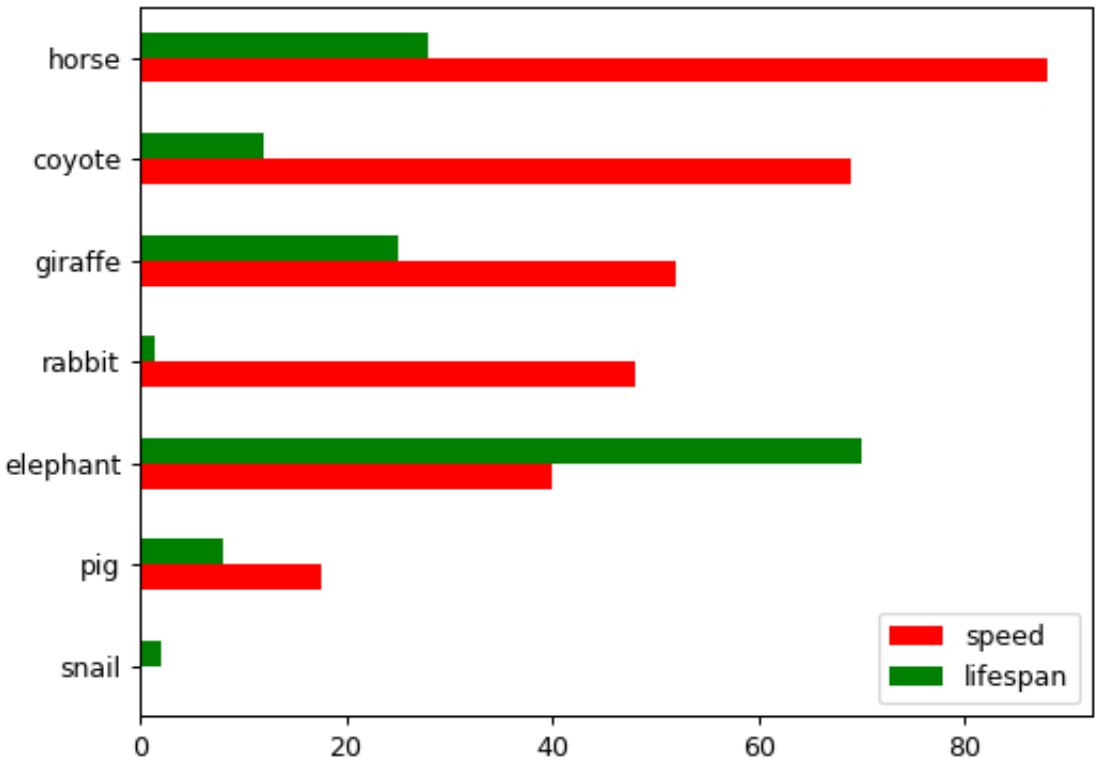
We can specify colors for each column

```
>>> ax = df.plot.barh(color={"speed": "red", "lifespan": "green"})
```


val
C
B
A
lab
0
5
10
15
20
25
30

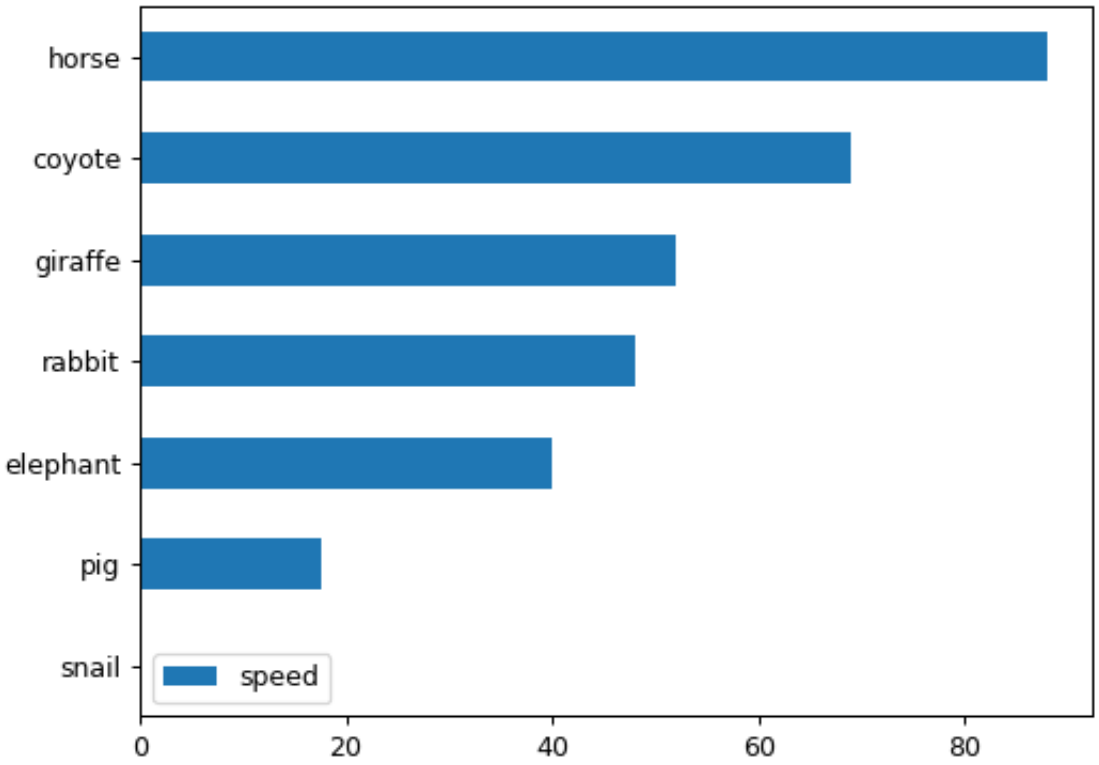

horse
coyote
giraffe
rabbit
elephant
pig
snail
0
20
40
60
80
speed
lifespan


horse
coyote
giraffe
rabbit
elephant
pig
snail
0
20
40
60
80
100
120
speed
lifespan


horse
coyote
giraffe
rabbit
elephant
pig
snail
0
20
40
60
80
speed
lifespan

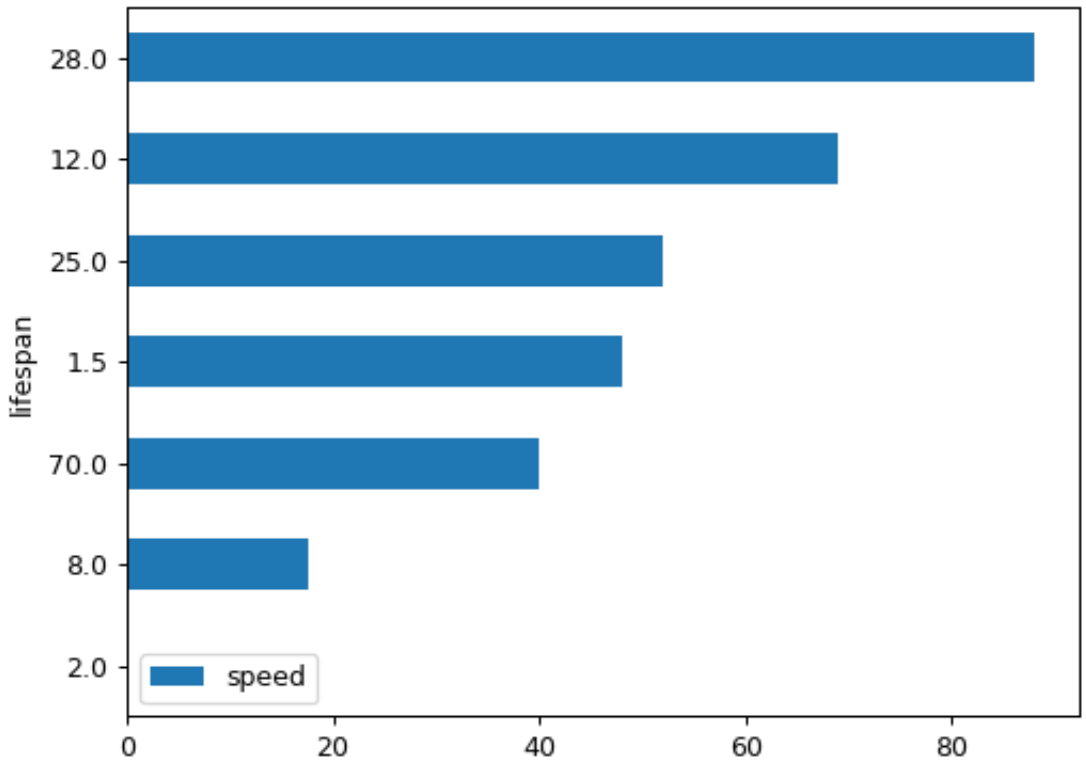
Plot a column of the DataFrame to a horizontal bar plot

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(y='speed')
```



Plot DataFrame versus the desired column

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...          'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(x='lifespan')
```


28.0
12.0
25.0
1.5
70.0
8.0
2.0
lifespan
speed
0
20
40
60
80

pandas.DataFrame.plot.box

DataFrame.plot.**box**(*by=None*, ***kwargs*)

Make a box plot of the DataFrame columns.

A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to 1.5*IQR (IQR = Q3 - Q1) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia's entry for boxplot.

A consideration when using this chart is that the box and the whiskers can overlap, which is very common when plotting small sets of data.

Parameters

by [str or sequence] Column in the DataFrame to group by.

****kwargs** Additional keywords are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or numpy.ndarray of them

See also:

DataFrame.boxplot Another method to draw a box plot.
Series.plot.box Draw a box plot from a Series object.
matplotlib.pyplot.boxplot Draw a box plot in matplotlib.

Examples

Draw a box plot from a DataFrame with four columns of randomly generated data.

```
>>> data = np.random.randn(25, 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'))
>>> ax = df.plot.box()
```

pandas.DataFrame.plot.density

DataFrame.plot.**density**(*bw_method=None*, *ind=None*, ***kwargs*)

Generate Kernel Density Estimate plot using Gaussian kernels.

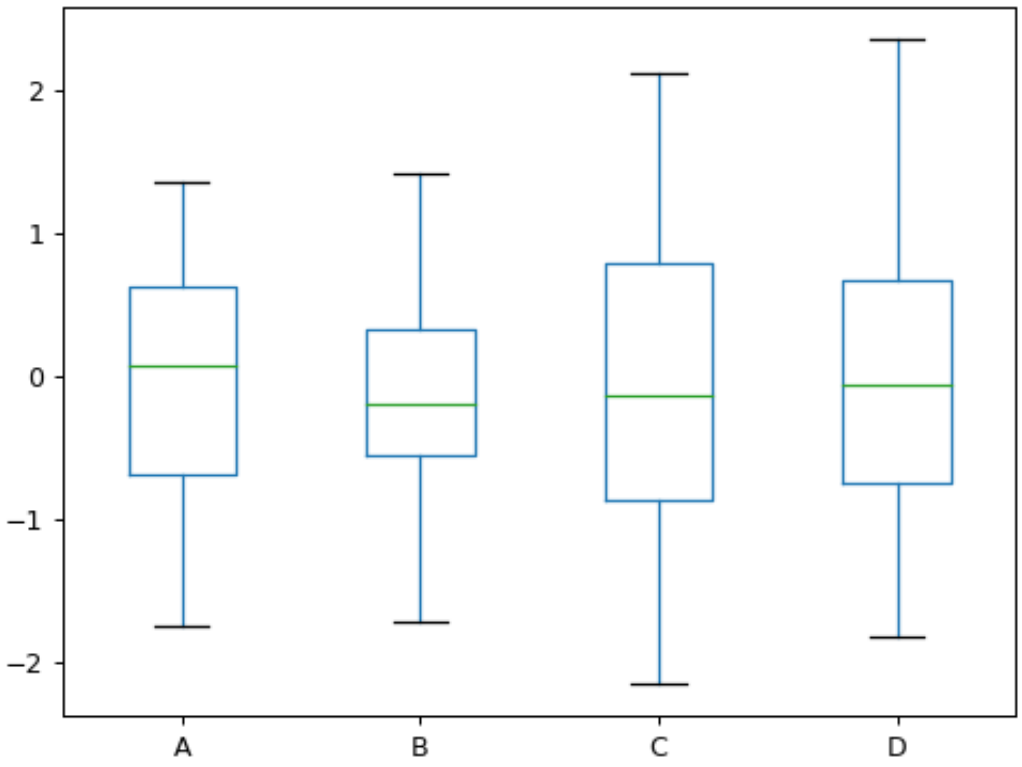
In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

Parameters

bw_method [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be 'scott', 'silverman', a scalar constant or a callable. If None (default), 'scott' is used. See scipy.stats.gaussian_kde for more information.

ind [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

****kwargs** Additional keyword arguments are documented in pandas.%(this-datatype)s.plot().


2
1
0
−1
−2
A
B
C
D

Returns

matplotlib.axes.Axes or numpy.ndarray of them

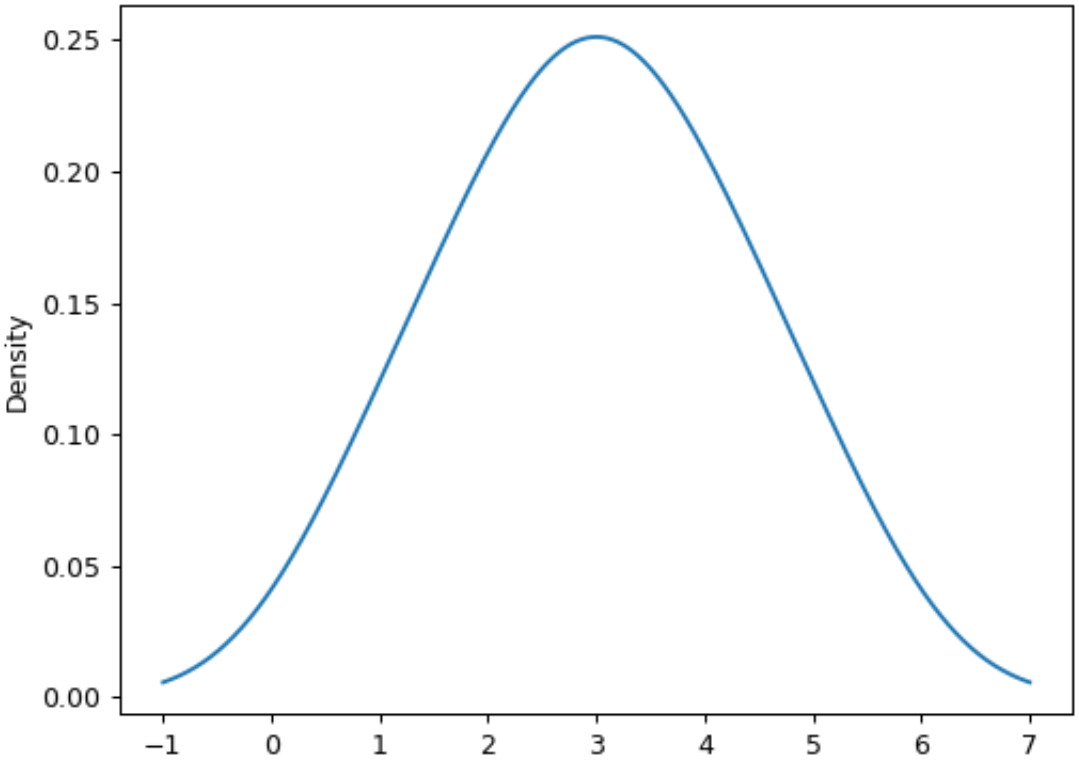
See also:

`scipy.stats.gaussian_kde` Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

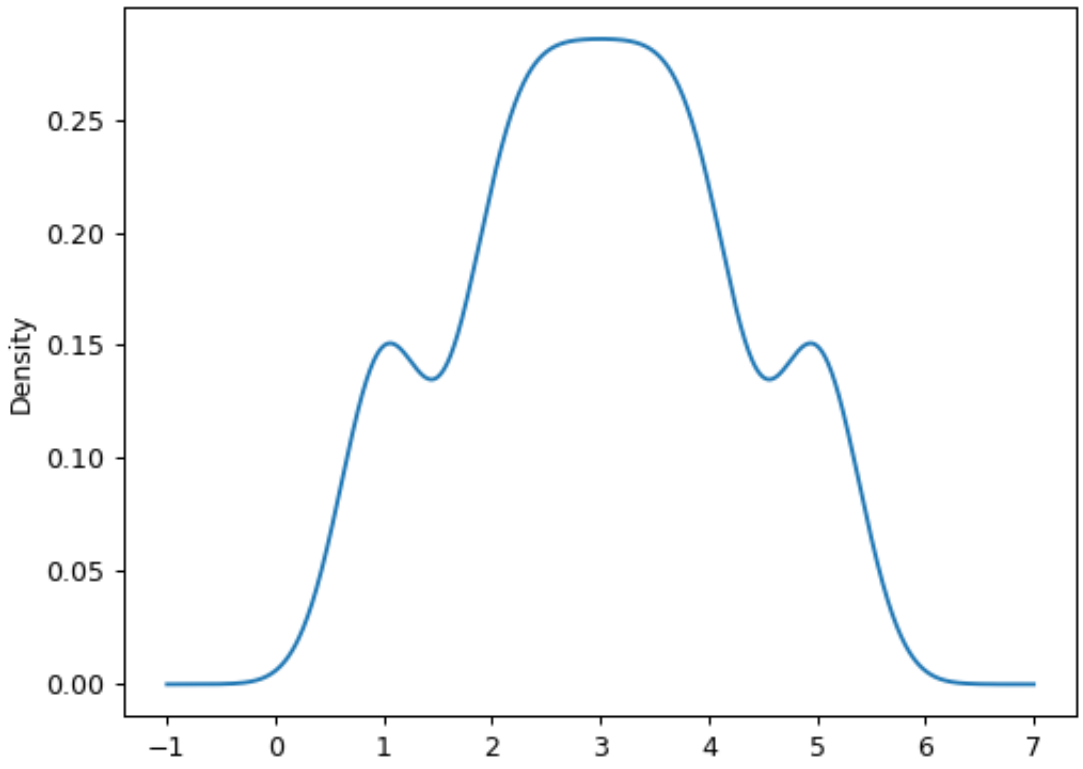


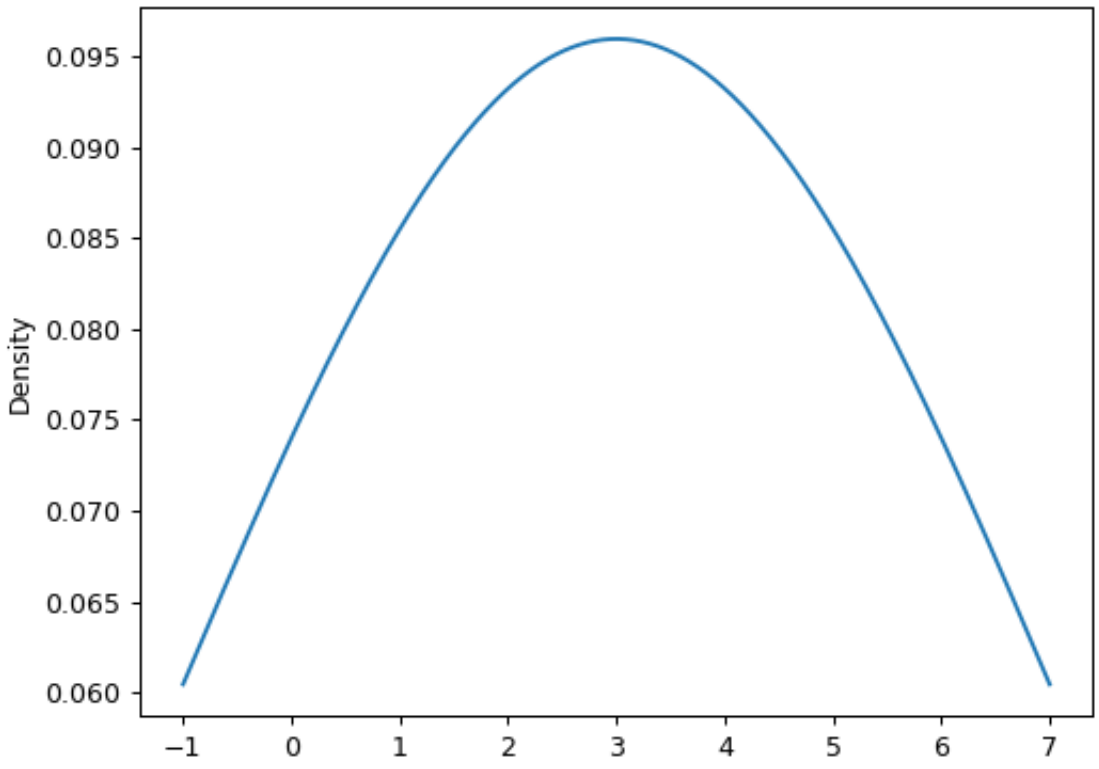
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

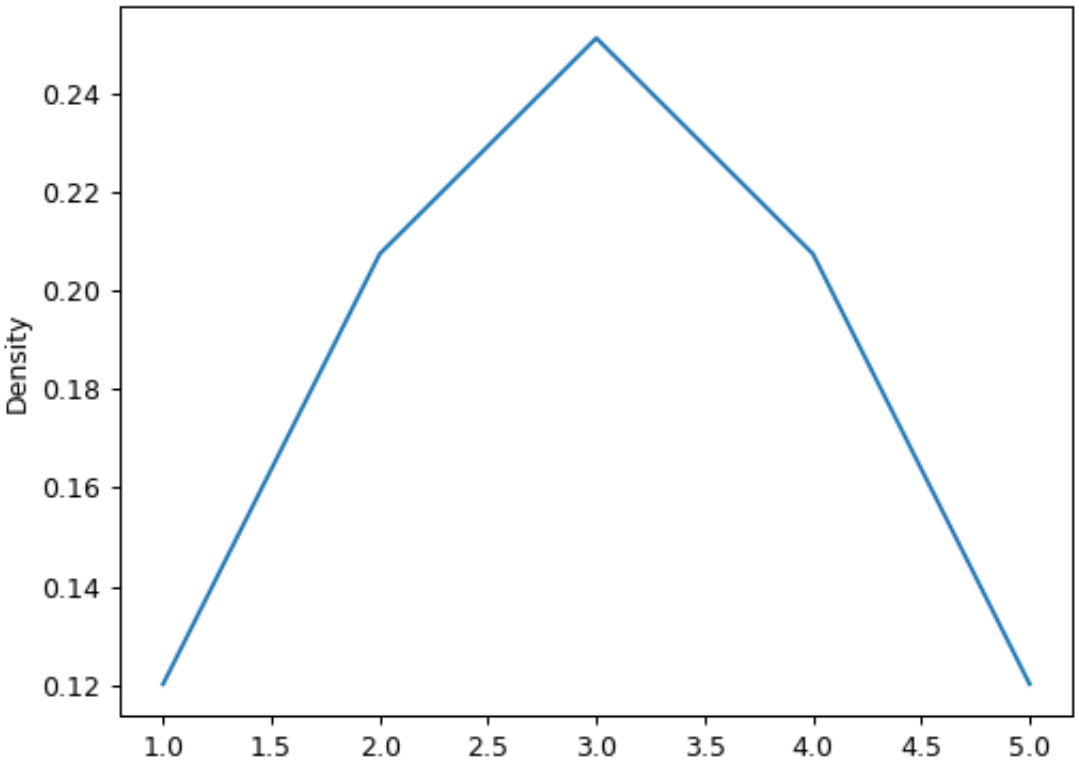
```
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:


Density
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7


0.095
0.090
0.085
0.080
0.075
0.070
0.065
0.060
Density
−1
0
1
2
3
4
5
6
7

```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```



For DataFrame, it works in the same way:

```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```

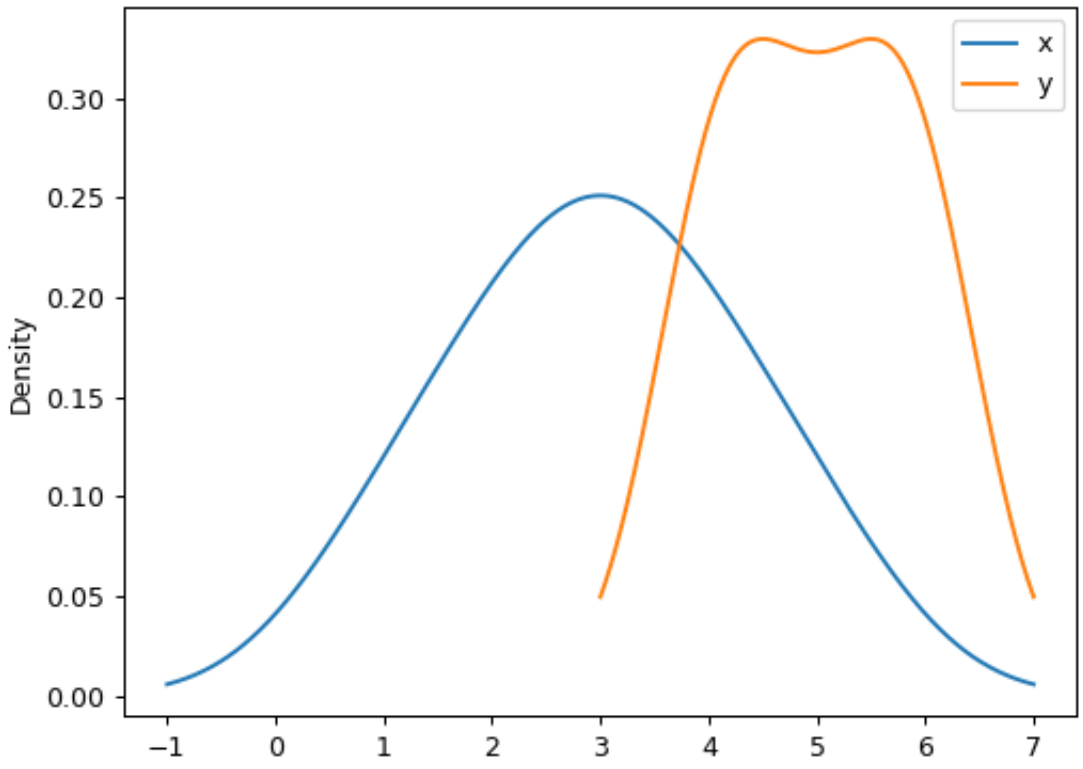
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

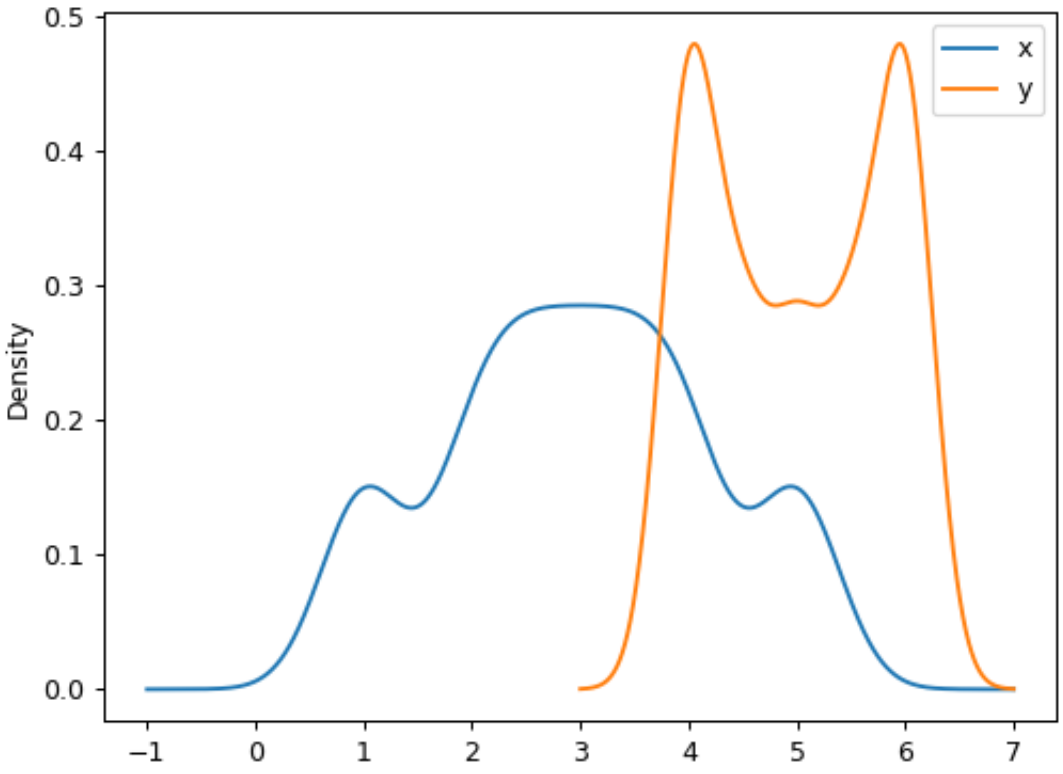
```
>>> ax = df.plot.kde(bw_method=0.3)
```

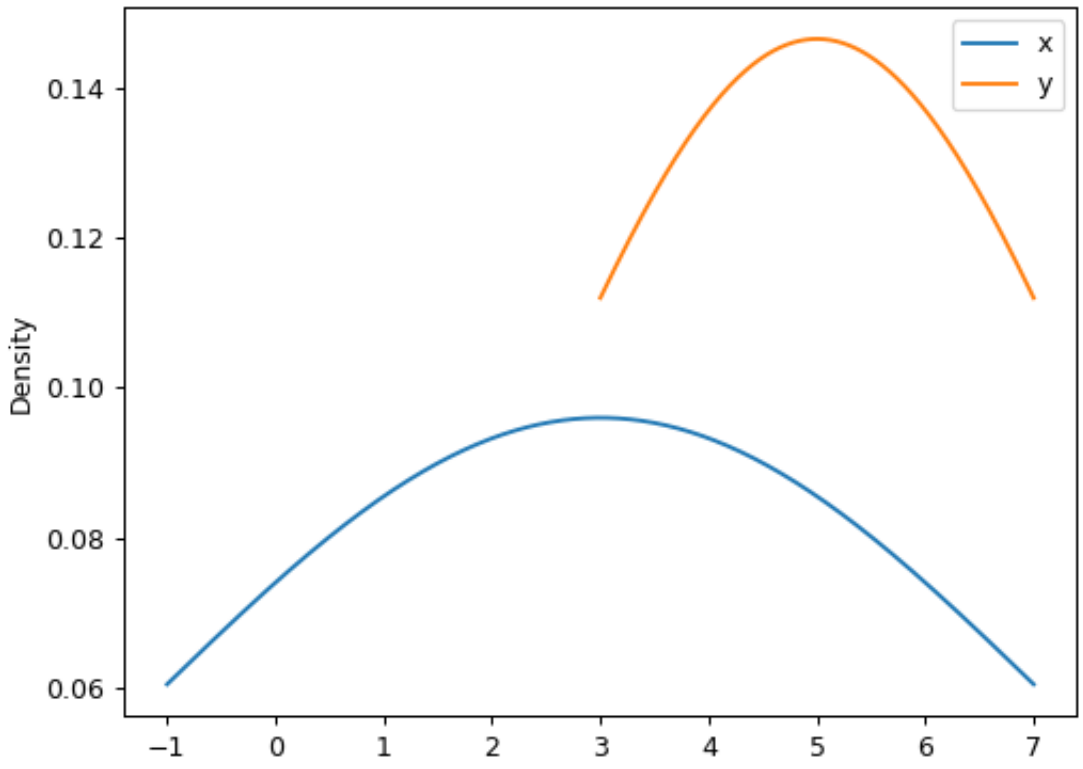
```
>>> ax = df.plot.kde(bw_method=3)
```

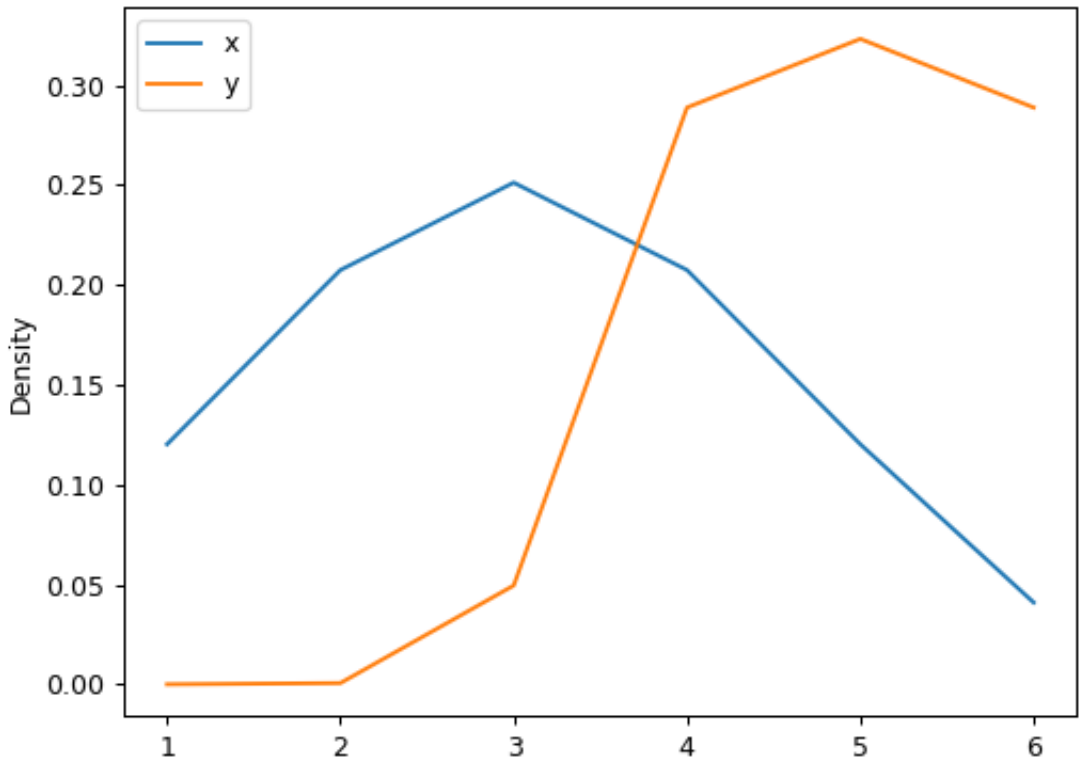
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```


x
y
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7


0.5
0.4
0.3
0.2
0.1
0.0
Density
−1
0
1
2
3
4
5
6
7
x
y


x
y
0.14
0.12
0.10
0.08
0.06
Density
−1
0
1
2
3
4
5
6
7


x
y
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Density
1
2
3
4
5
6

pandas.DataFrame.plot.hexbin

DataFrame.plot.**hexbin**(*x*, *y*, *C=None*, *reduce_C_function=None*, *gridsize=None*, ***kwargs*)

Generate a hexagonal binning plot.

Generate a hexagonal binning plot of *x* versus *y*. If *C* is *None* (the default), this is a histogram of the number of occurrences of the observations at `(x[i], y[i])`.

If *C* is specified, specifies values at given coordinates `(x[i], y[i])`. These values are accumulated for each hexagonal bin and then reduced according to *reduce_C_function*, having as default the NumPy's mean function (`numpy.mean()`). (If *C* is specified, it must also be a 1-D sequence of the same length as *x* and *y*, or a column label.)

Parameters

x [int or str] The column label or position for x points.

y [int or str] The column label or position for y points.

C [int or str, optional] The column label or position for the value of *(x, y)* point.

reduce_C_function [callable, default *np.mean*] Function of one argument that reduces all the values in a bin to a single number (e.g. *np.mean*, *np.max*, *np.sum*, *np.std*).

gridsize [int or tuple of (int, int), default 100] The number of hexagons in the x-direction. The corresponding number of hexagons in the y-direction is chosen in a way that the hexagons are approximately regular. Alternatively, gridsize can be a tuple with two elements specifying the number of hexagons in the x-direction and the y-direction.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.AxesSubplot The matplotlib `Axes` on which the hexbin is plotted.

See also:

DataFrame.plot Make plots of a DataFrame.

matplotlib.pyplot.hexbin Hexagonal binning plot using matplotlib, the matplotlib function that is used under the hood.

Examples

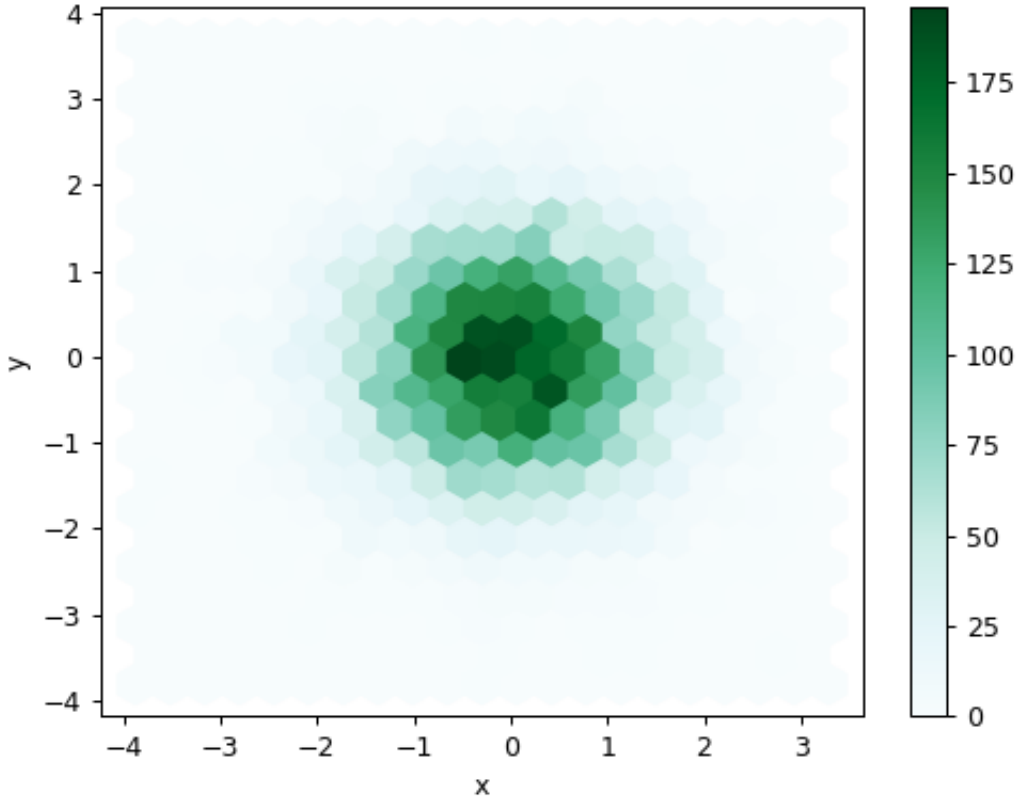
The following examples are generated with random data from a normal distribution.

```
>>> n = 10000
>>> df = pd.DataFrame({'x': np.random.randn(n),
...                    'y': np.random.randn(n)})
>>> ax = df.plot.hexbin(x='x', y='y', gridsize=20)
```

The next example uses *C* and *np.sum* as *reduce_C_function*. Note that *'observations'* values ranges from 1 to 5 but the result plot shows values up to more than 25. This is because of the *reduce_C_function*.

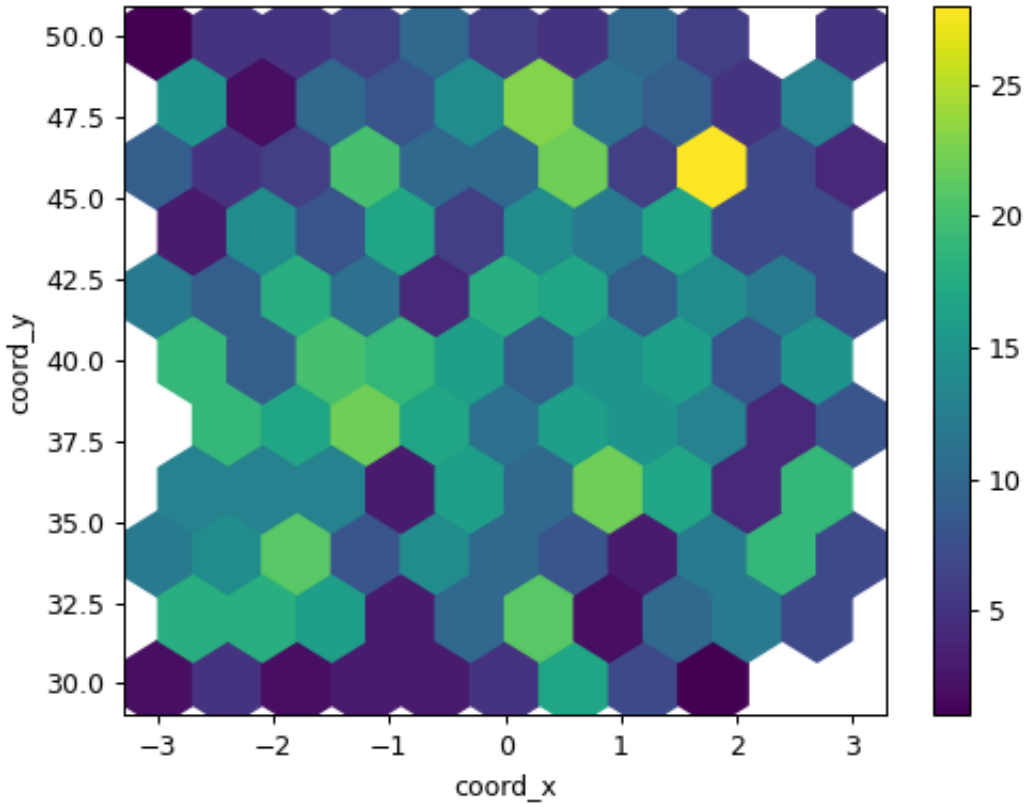
```
>>> n = 500
>>> df = pd.DataFrame({
...     'coord_x': np.random.uniform(-3, 3, size=n),
...     'coord_y': np.random.uniform(30, 50, size=n),
...     'observations': np.random.randint(1,5, size=n)
...     })
>>> ax = df.plot.hexbin(x='coord_x',
...                     y='coord_y',
```

(continues on next page)


4
3
2
1
0
−1
−2
−3
−4
y
−4
−3
−2
−1
0
1
2
3
x
175
150
125
100
75
50
25
0

(continued from previous page)

```
...                     C='observations',
...                     reduce_C_function=np.sum,
...                     gridsize=10,
...                     cmap="viridis")
```



pandas.DataFrame.plot.hist

`DataFrame.plot.`**`hist`**(*by=None*, *bins=10*, ***kwargs*)

Draw one histogram of the DataFrame's columns.

A histogram is a representation of the distribution of data. This function groups the values of all given Series in the DataFrame into bins and draws all bins in one `matplotlib.axes.Axes`. This is useful when the DataFrame's Series are in a similar scale.

Parameters

by [str or sequence, optional] Column in the DataFrame to group by.

bins [int, default 10] Number of histogram bins to be used.

****kwargs** Additional keyword arguments are documented in *`DataFrame.plot()`*.

Returns

class:*matplotlib.AxesSubplot* Return a histogram plot.

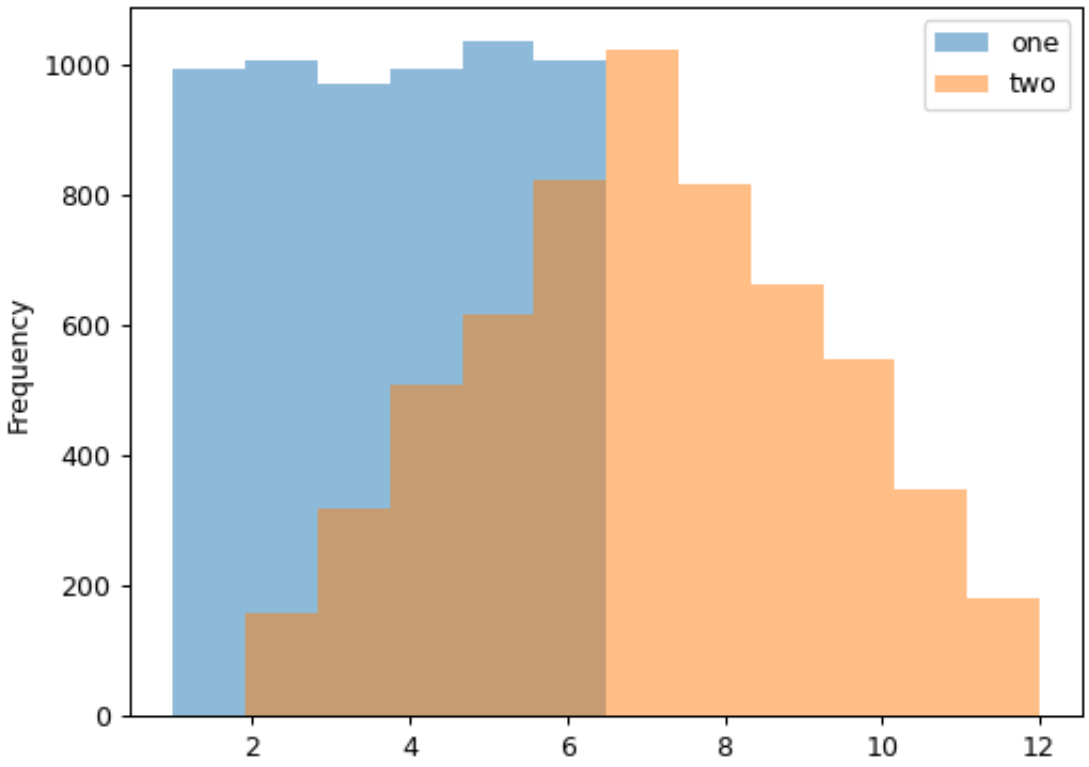
See also:

DataFrame.hist Draw histograms per DataFrame's Series.
Series.hist Draw a histogram with Series' data.

Examples

When we draw a dice 6000 times, we expect to get each value around 1000 times. But when we draw two dices and sum the result, the distribution is going to be quite different. A histogram illustrates those distributions.

```
>>> df = pd.DataFrame(
...     np.random.randint(1, 7, 6000),
...     columns = ['one'])
>>> df['two'] = df['one'] + np.random.randint(1, 7, 6000)
>>> ax = df.plot.hist(bins=12, alpha=0.5)
```



pandas.DataFrame.plot.kde

DataFrame.plot.**kde**(*bw_method=None*, *ind=None*, ***kwargs*)

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

Parameters

bw_method [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be 'scott', 'silverman', a scalar constant or a callable. If None (default), 'scott' is used. See `scipy.stats.gaussian_kde` for more information.

ind [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

****kwargs** Additional keyword arguments are documented in `pandas.%(this-datatype)s.plot()`.

Returns

matplotlib.axes.Axes or numpy.ndarray of them

See also:

scipy.stats.gaussian_kde Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

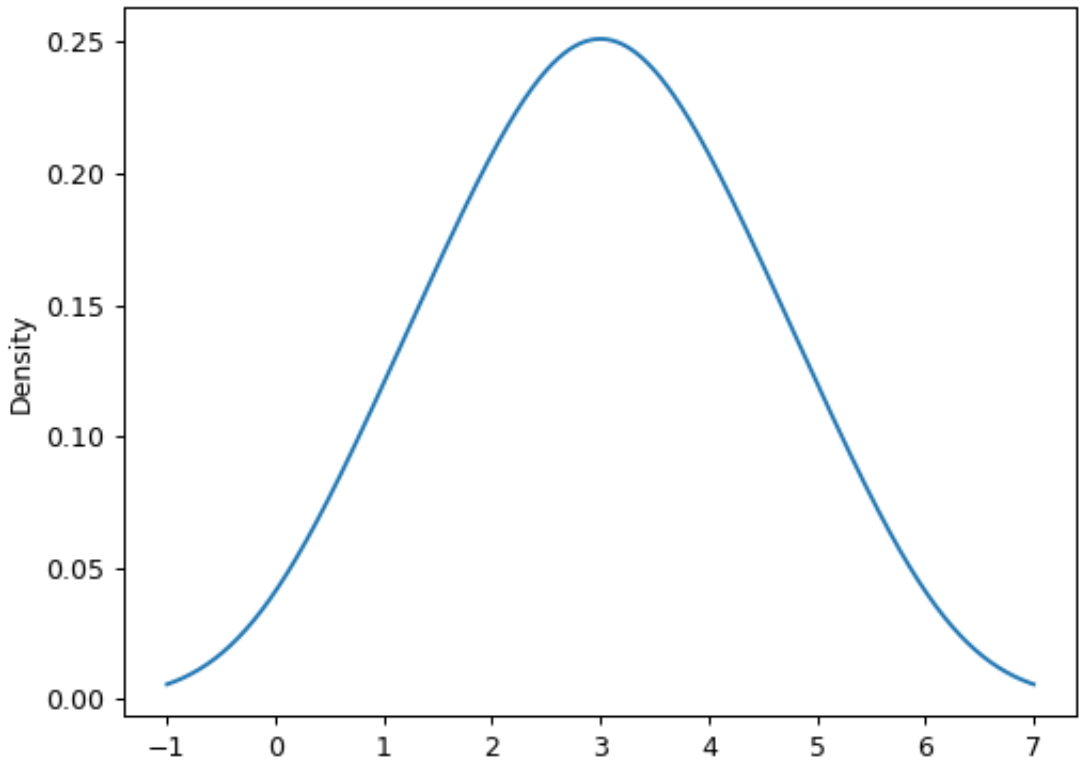
```
>>> ax = s.plot.kde(bw_method=3)
```

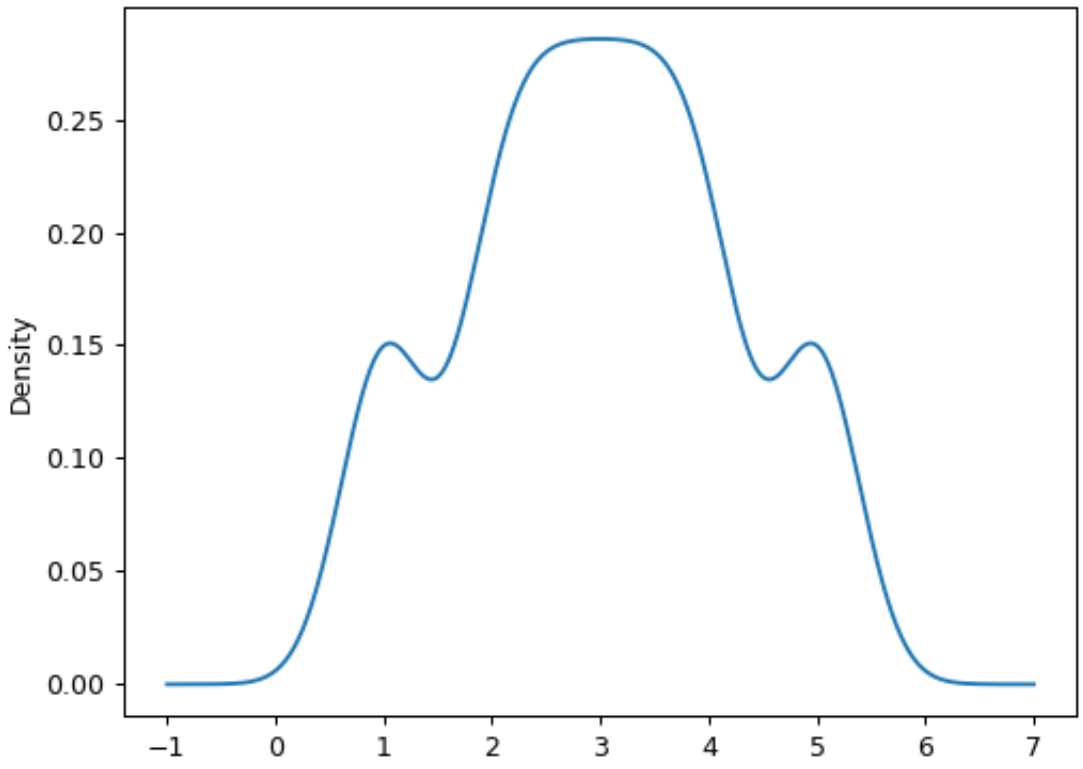
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

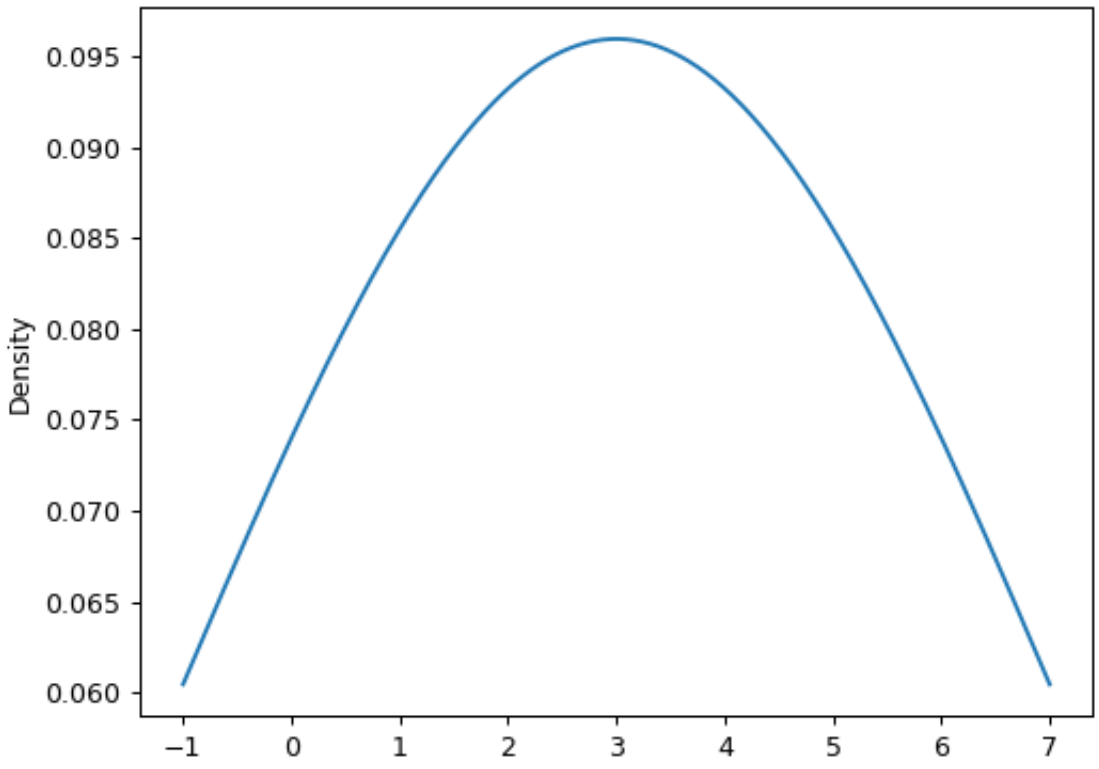
```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```

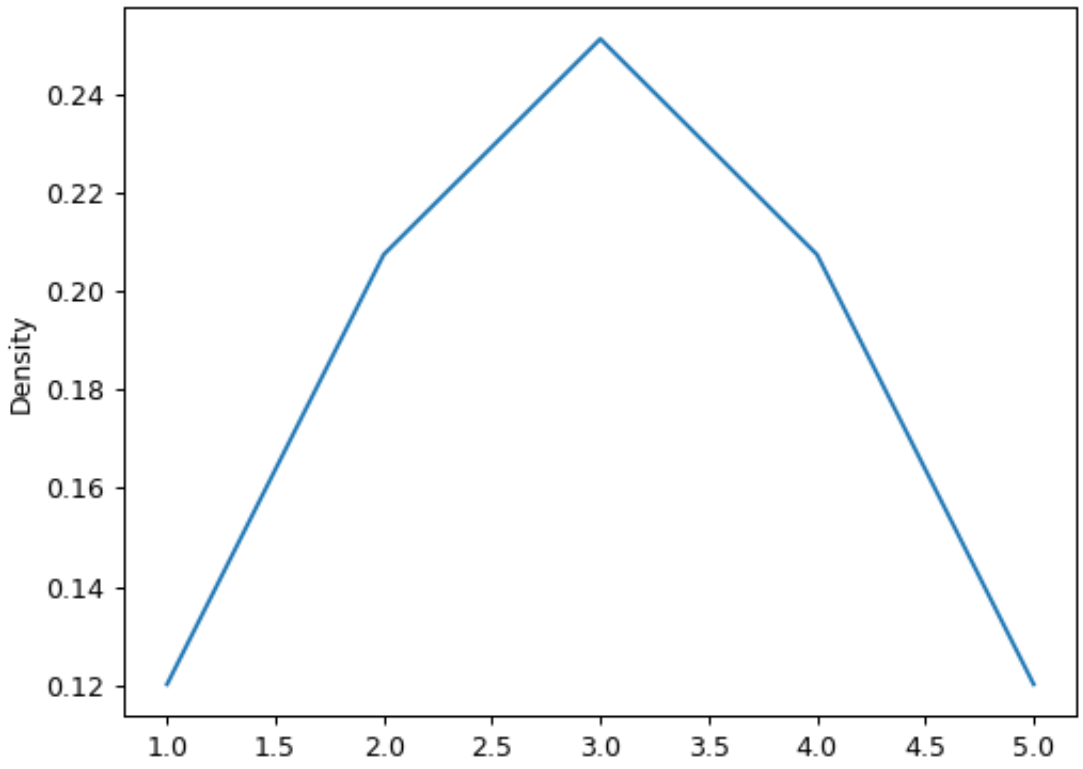
For DataFrame, it works in the same way:

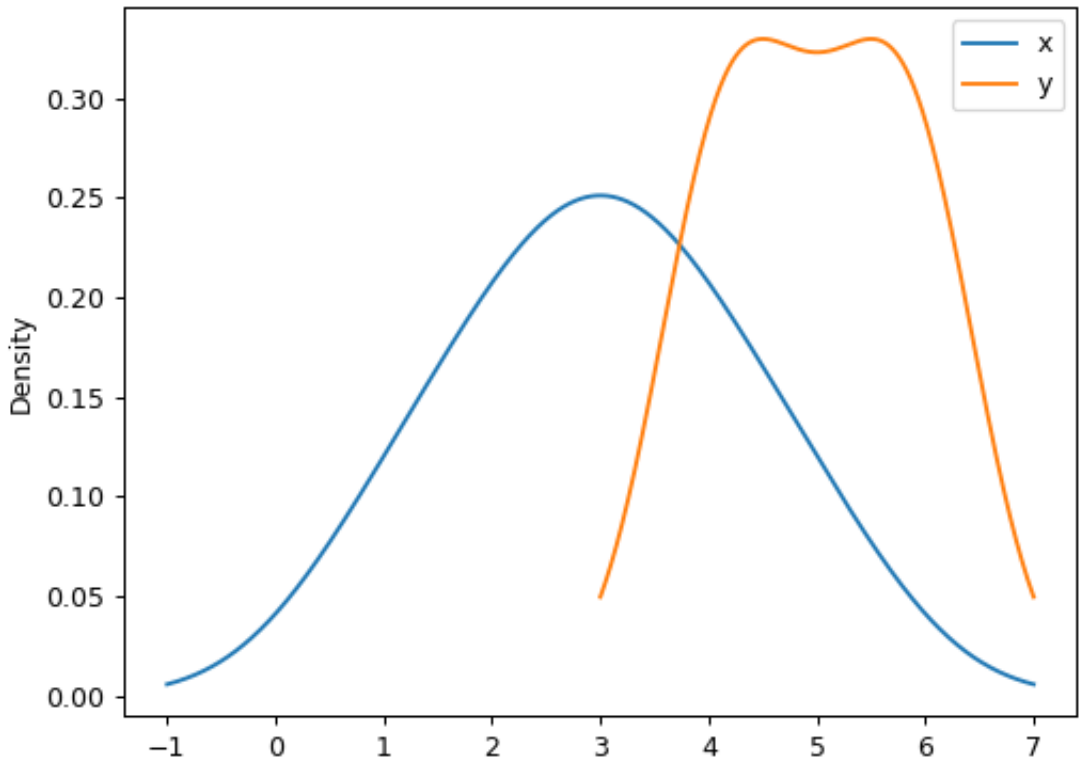
```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```


0.25
0.20
0.15
0.10
0.05
0.00
Density
−1
0
1
2
3
4
5
6
7


Density
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7

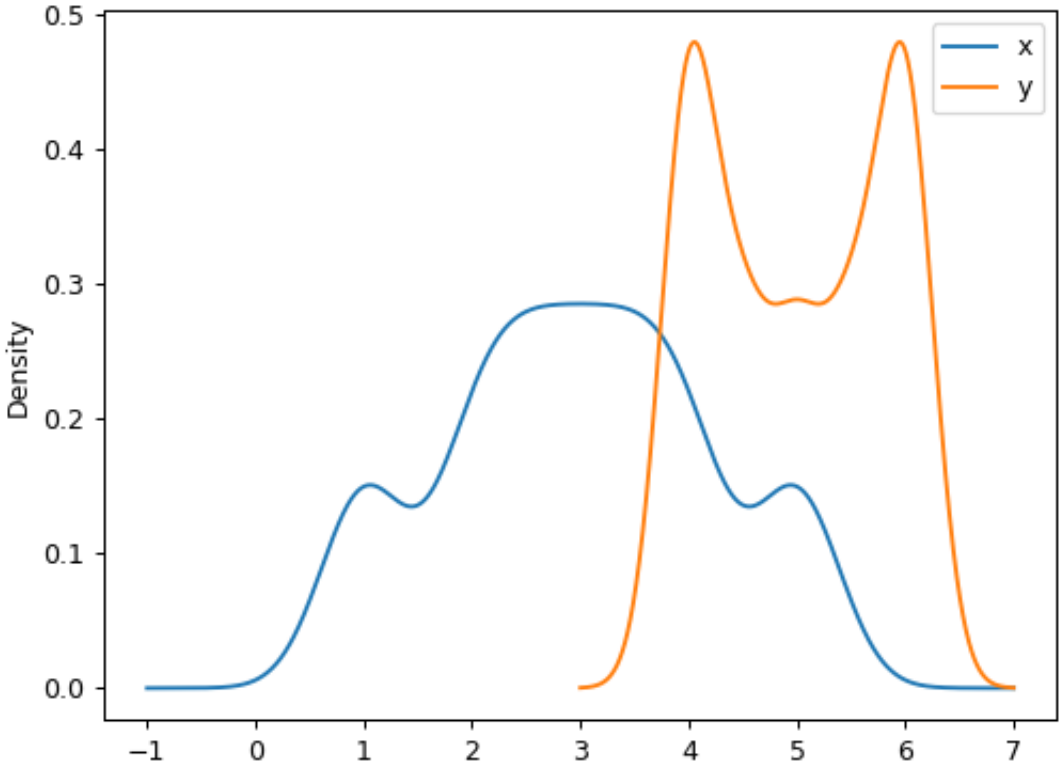

Density
0.095
0.090
0.085
0.080
0.075
0.070
0.065
0.060
−1
0
1
2
3
4
5
6
7


Density
0.24
0.22
0.20
0.18
0.16
0.14
0.12
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


x
y
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
6
7

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = df.plot.kde(bw_method=0.3)
```




```
>>> ax = df.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```

pandas.DataFrame.plot.line

`DataFrame.plot.`**`line`**(*x=None*, *y=None*, ***kwargs*)

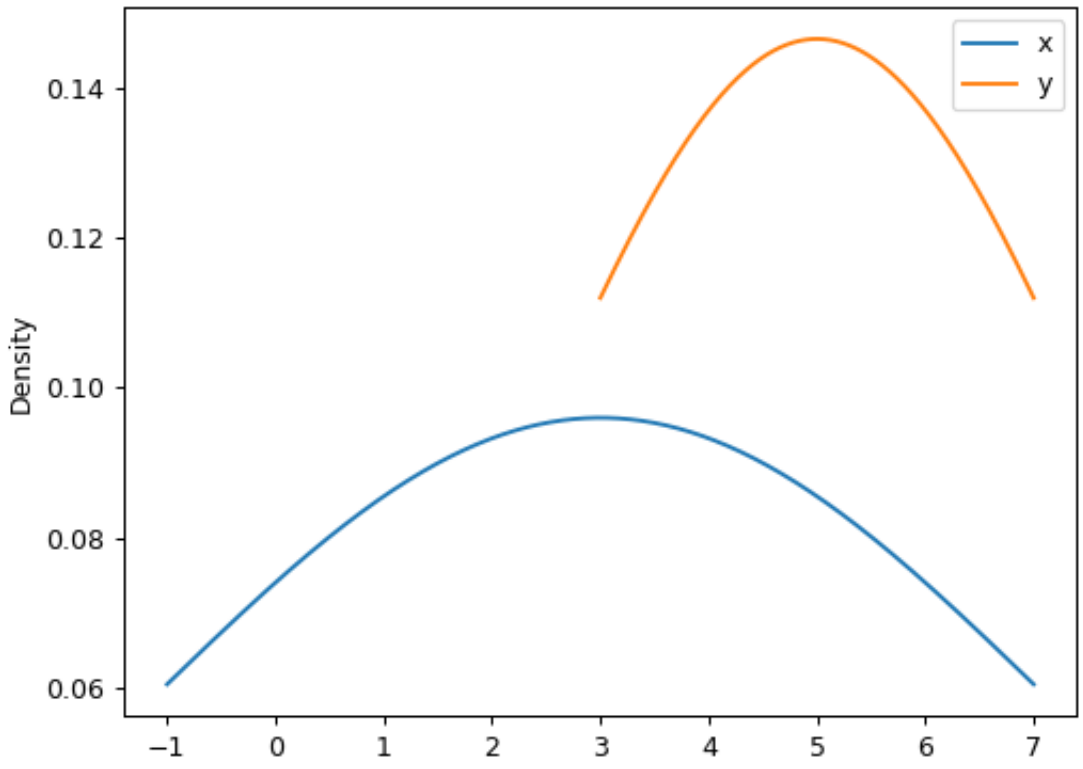
Plot Series or DataFrame as lines.

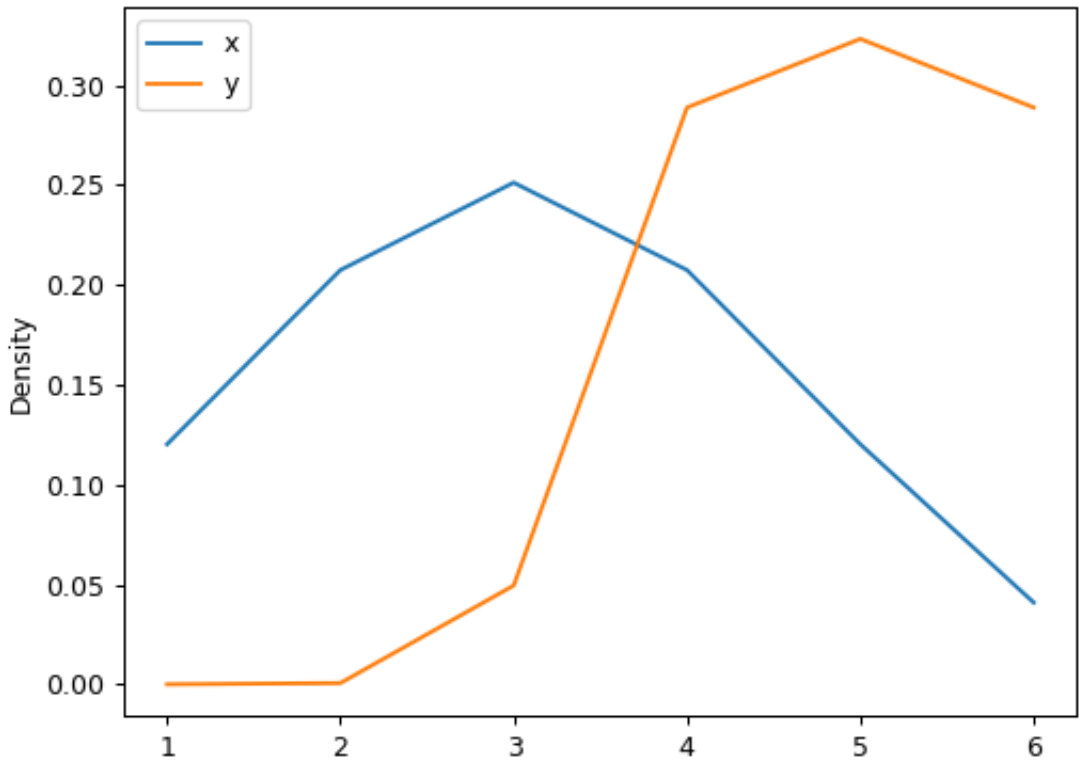
This function is useful to plot lines using DataFrame's values as coordinates.

Parameters

x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.


x
y
0.14
0.12
0.10
0.08
0.06
Density
−1
0
1
2
3
4
5
6
7


x
y
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
1
2
3
4
5
6

color [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:

- **A single color string referred to by name, RGB or RGBA code,** for instance 'red' or '#a98d19'.
- **A sequence of color strings referred to by name, RGB or RGBA** code, which will be used for each column recursively. For instance ['green','yellow'] each column's line will be filled in green or yellow, alternatively.
- **A dict of the form {column name** [color}, so that each column will be] colored accordingly. For example, if your columns are called *a* and *b*, then passing {'a': 'green', 'b': 'red'} will color lines for column *a* in green and lines for column *b* in red.

New in version 1.1.0.

****kwargs** Additional keyword arguments are documented in *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

See also:

`matplotlib.pyplot.plot` Plot y versus x as lines and/or markers.

Examples

```
>>> s = pd.Series([1, 3, 2])
>>> s.plot.line()
```

The following example shows the populations for some animals over the years.

```
>>> df = pd.DataFrame({
...    'pig': [20, 18, 489, 675, 1776],
...    'horse': [4, 25, 281, 600, 1900]
...    }, index=[1990, 1997, 2003, 2009, 2014])
>>> lines = df.plot.line()
```

An example with subplots, so an array of axes is returned.

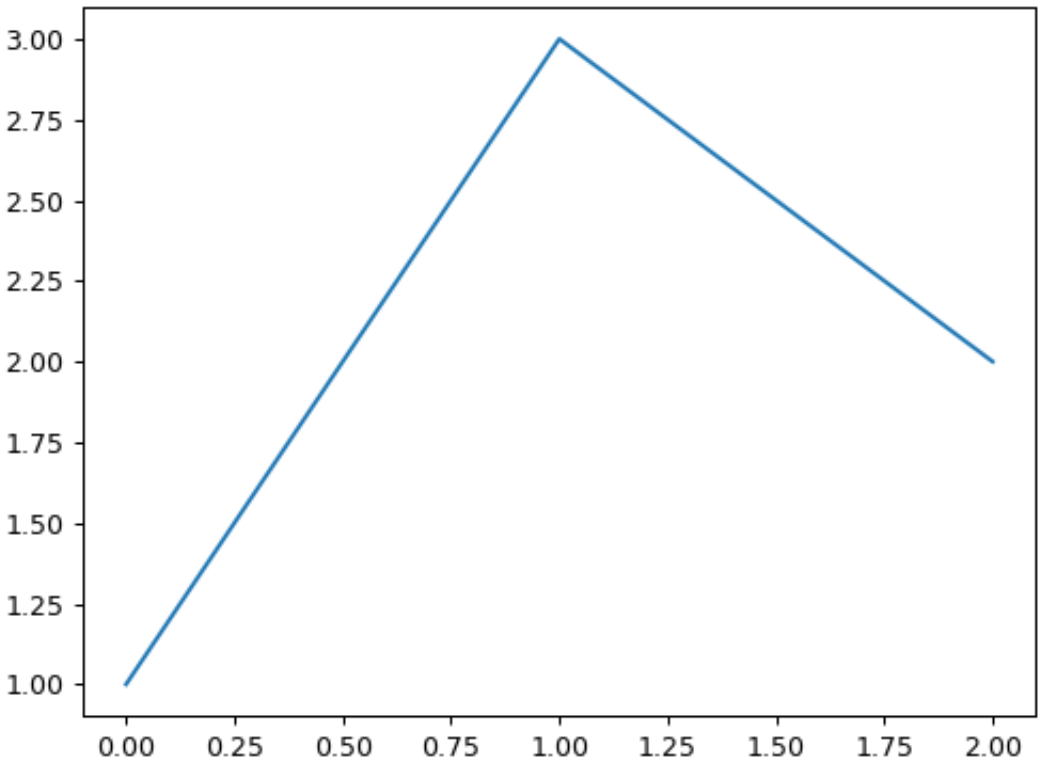
```
>>> axes = df.plot.line(subplots=True)
>>> type(axes)
<class 'numpy.ndarray'>
```

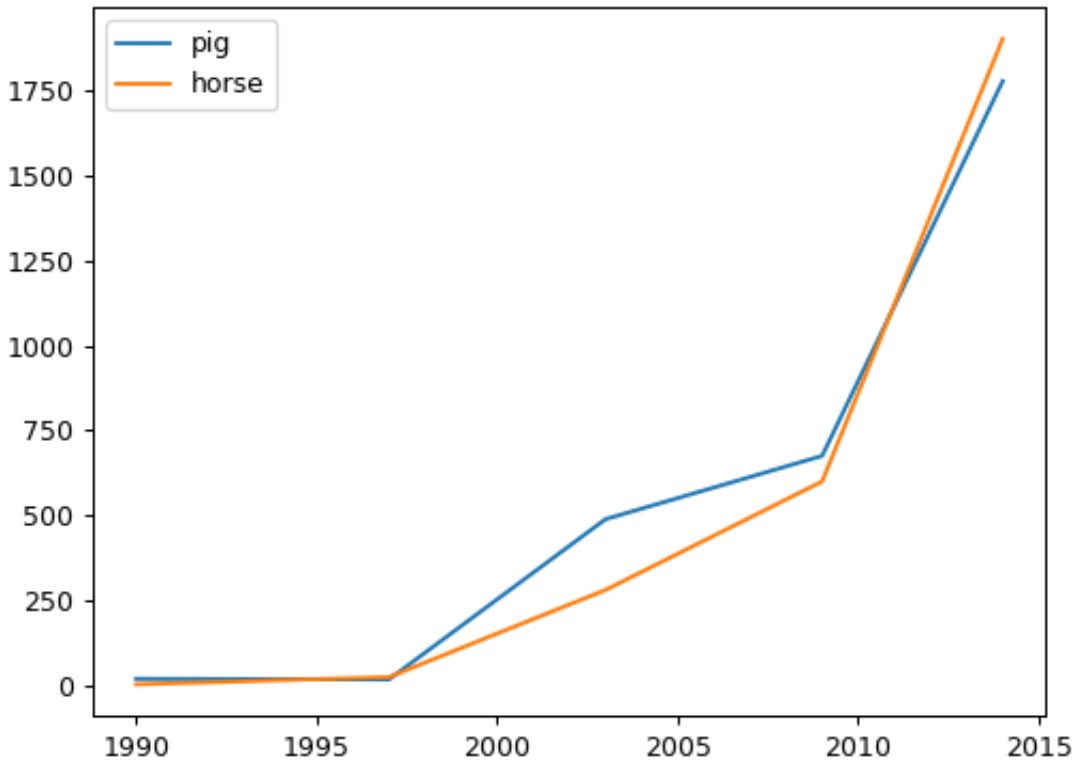
Let's repeat the same example, but specifying colors for each column (in this case, for each animal).

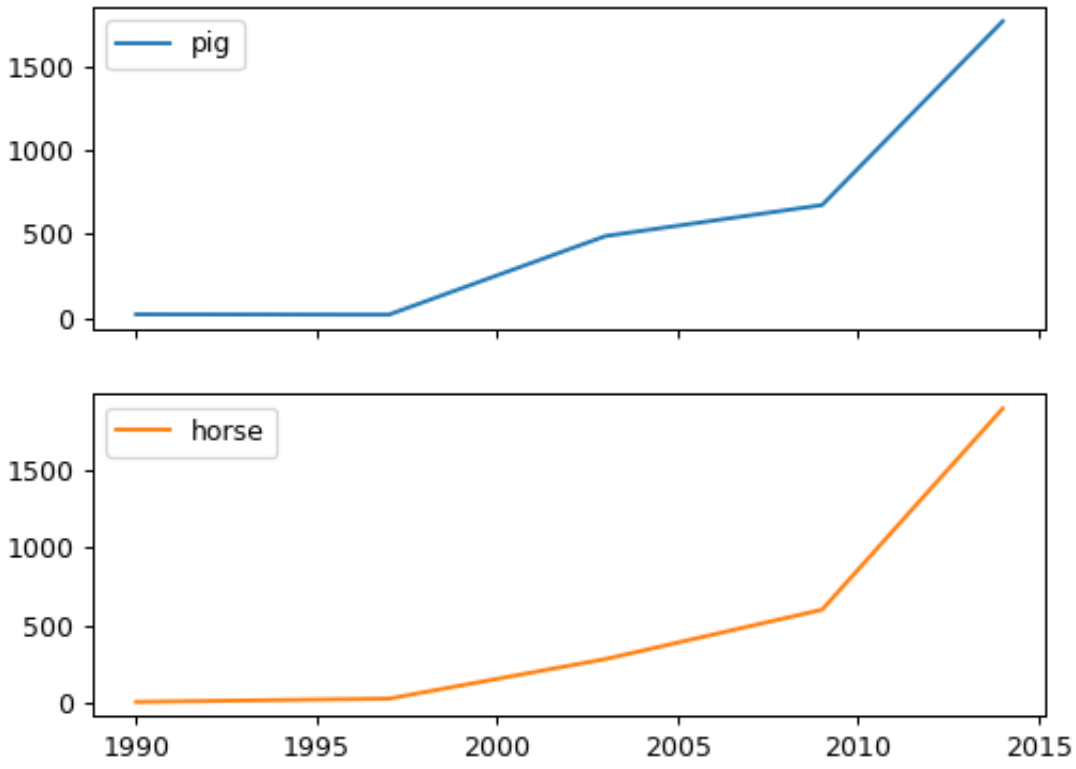
```
>>> axes = df.plot.line(
...     subplots=True, color={"pig": "pink", "horse": "#742802"}
... )
```

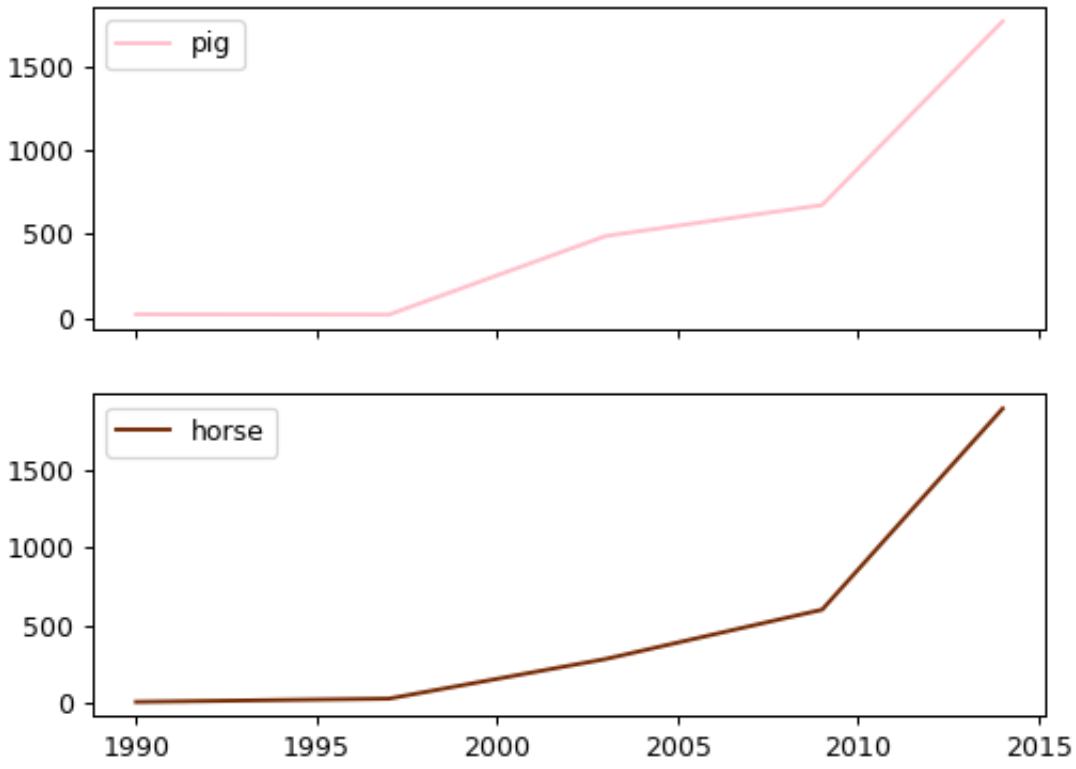
The following example shows the relationship between both populations.

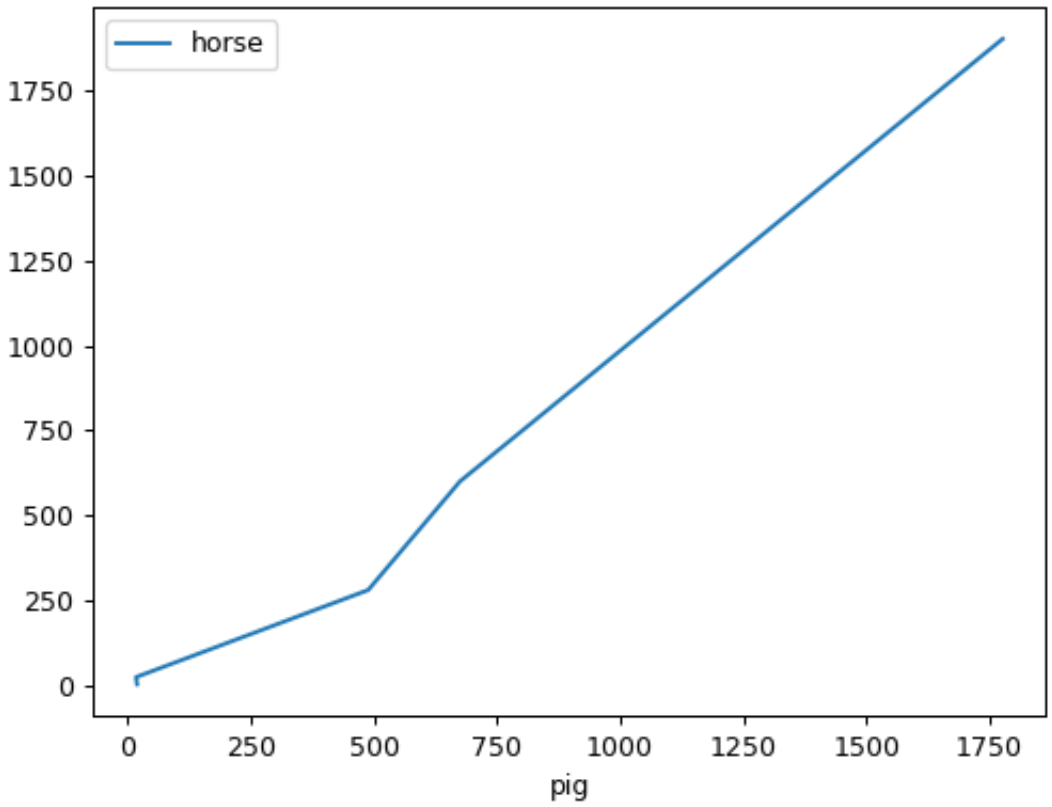
```
>>> lines = df.plot.line(x='pig', y='horse')
```


3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


pig
horse
1750
1500
1250
1000
750
500
250
0
1990
1995
2000
2005
2010
2015


pig
1500
1000
500
0
horse
1500
1000
500
0
1990
1995
2000
2005
2010
2015


pig
1500
1000
500
0
horse
1500
1000
500
0
1990
1995
2000
2005
2010
2015


horse
1750
1500
1250
1000
750
500
250
0
0
250
500
750
1000
1250
1500
1750
pig

pandas.DataFrame.plot.pie

DataFrame.plot.**pie**(***kwargs*)

Generate a pie plot.

A pie plot is a proportional representation of the numerical data in a column. This function wraps `matplotlib.pyplot.pie()` for the specified column. If no column reference is passed and `subplots=True` a pie plot is drawn for each numerical column independently.

Parameters

y [int or label, optional] Label or position of the column to plot. If not provided, `subplots=True` argument must be passed.

****kwargs** Keyword arguments to pass on to *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or np.ndarray of them A NumPy array is returned when *subplots* is True.

See also:

Series.plot.pie Generate a pie plot for a Series.
DataFrame.plot Make plots of a DataFrame.

Examples

In the example below we have a DataFrame with the information about planet's mass and radius. We pass the 'mass' column to the pie function to get a pie plot.

```
>>> df = pd.DataFrame({'mass': [0.330, 4.87 , 5.97],
...                    'radius': [2439.7, 6051.8, 6378.1]},
...                   index=['Mercury', 'Venus', 'Earth'])
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
```

```
>>> plot = df.plot.pie(subplots=True, figsize=(11, 6))
```

pandas.DataFrame.plot.scatter

DataFrame.plot.**scatter**(*x*, *y*, *s=None*, *c=None*, ***kwargs*)

Create a scatter plot with varying marker point size and color.

The coordinates of each point are defined by two dataframe columns and filled circles are used to represent each point. This kind of plot is useful to see complex correlations between two variables. Points could be for instance natural 2D coordinates like longitude and latitude in a map or, in general, any pair of metrics that can be plotted against each other.

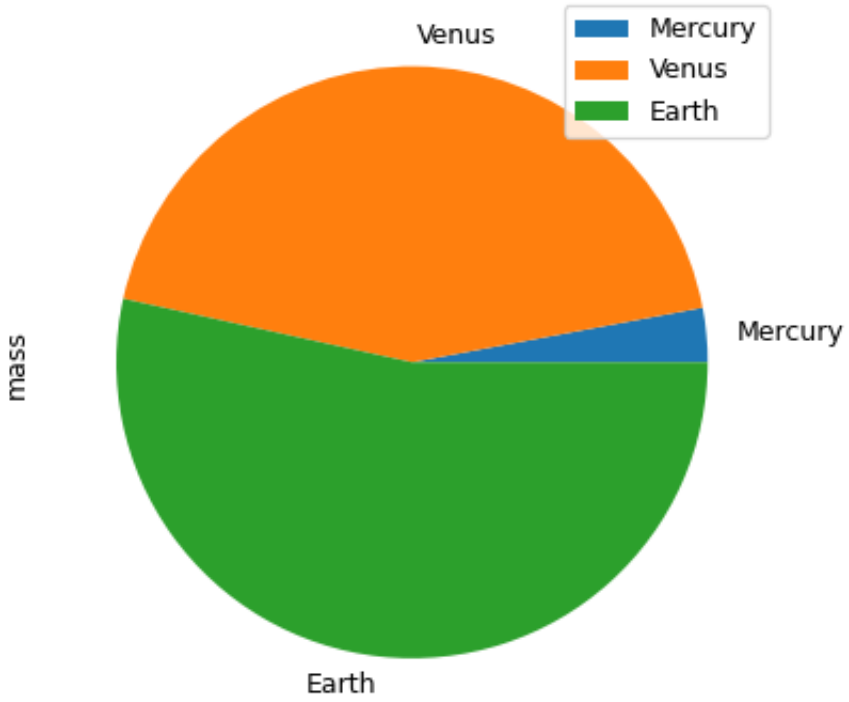
Parameters

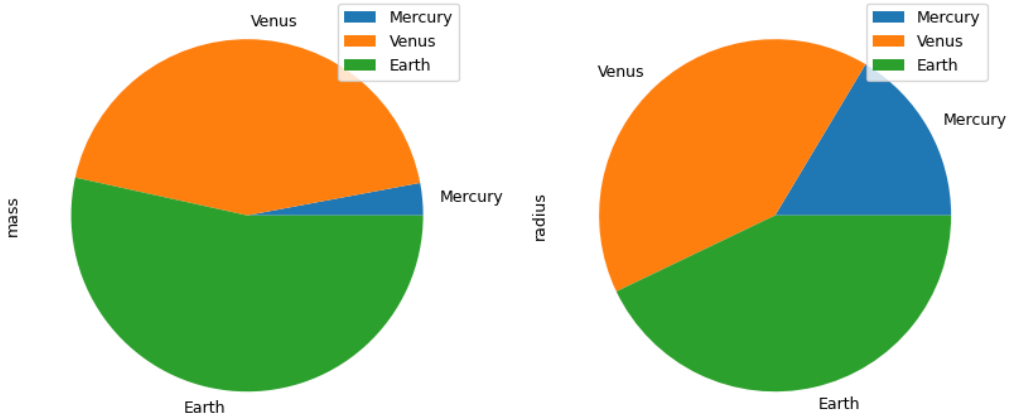
x [int or str] The column name or column position to be used as horizontal coordinates for each point.

y [int or str] The column name or column position to be used as vertical coordinates for each point.

s [str, scalar or array_like, optional] The size of each point. Possible values are:

- A string with the name of the column to be used for marker's size.
- A single scalar so all points have the same size.


Venus
Mercury
Venus
Earth
mass
Mercury
Earth


Venus
Mercury
Venus
Earth
mass
Mercury
Earth
Venus
Mercury
Venus
Earth
Mercury
radius
Earth

- A sequence of scalars, which will be used for each point's size recursively. For instance, when passing [2,14] all points size will be either 2 or 14, alternatively.

  Changed in version 1.1.0.

c [str, int or array_like, optional] The color of each point. Possible values are:

- A single color string referred to by name, RGB or RGBA code, for instance 'red' or '#a98d19'.
- A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each point's color recursively. For instance ['green','yellow'] all points will be filled in green or yellow, alternatively.
- A column name or position whose values will be used to color the marker points according to a colormap.

****kwargs** Keyword arguments to pass on to *DataFrame.plot()*.

Returns

matplotlib.axes.Axes or numpy.ndarray of them

See also:

matplotlib.pyplot.scatter Scatter plot using multiple input data formats.

Examples

Let's see how to draw a scatter plot using coordinates from the values in a DataFrame's columns.

```
>>> df = pd.DataFrame([[5.1, 3.5, 0], [4.9, 3.0, 0], [7.0, 3.2, 1],
...                    [6.4, 3.2, 1], [5.9, 3.0, 2]],
...                   columns=['length', 'width', 'species'])
>>> ax1 = df.plot.scatter(x='length',
...                       y='width',
...                       c='DarkBlue')
```

And now with the color determined by a column as well.

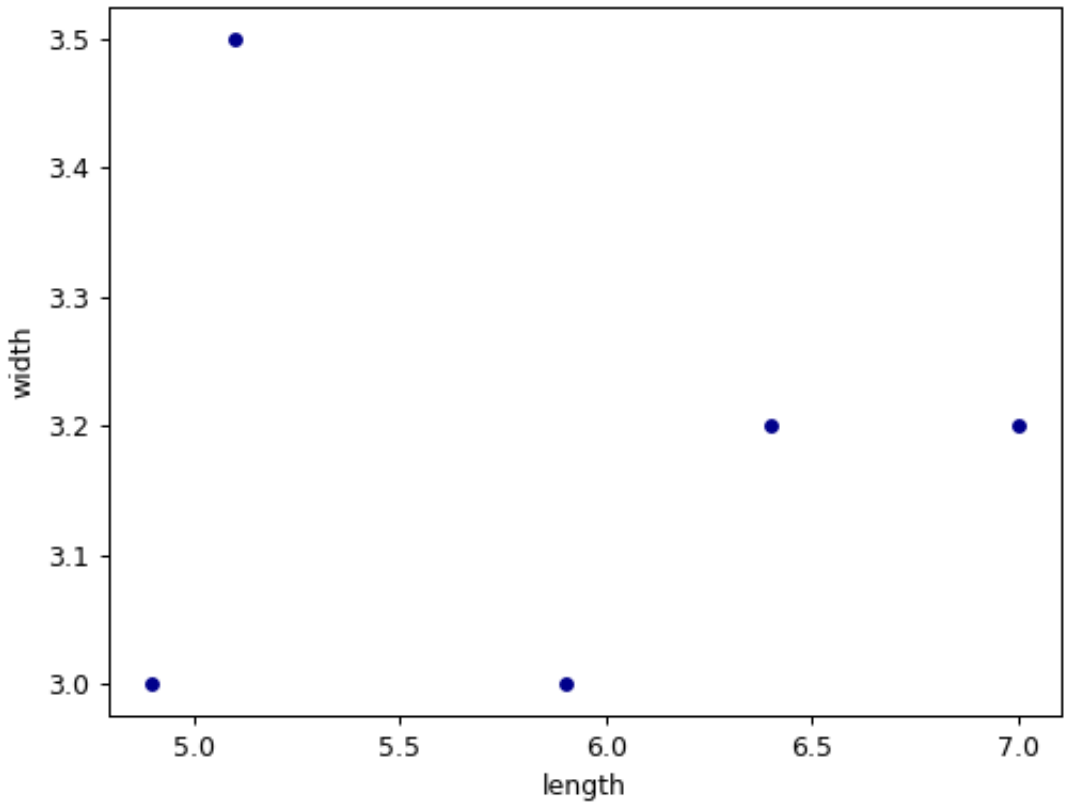
```
>>> ax2 = df.plot.scatter(x='length',
...                       y='width',
...                       c='species',
...                       colormap='viridis')
```

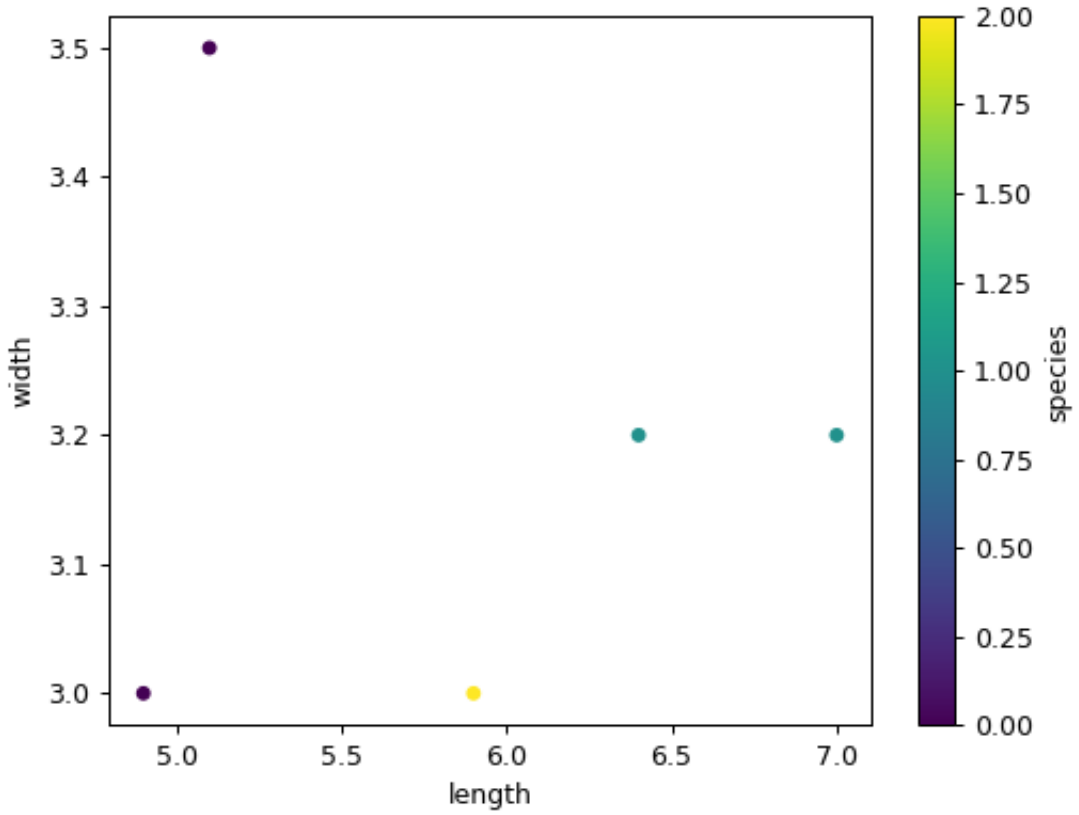
DataFrame.boxplot([column, by, ax, ...])	Make a box plot from DataFrame columns.
DataFrame.hist([column, by, grid, ...])	Make a histogram of the DataFrame's.

3.4.16 Sparse accessor

Sparse-dtype specific methods and attributes are provided under the `DataFrame.sparse` accessor.

DataFrame.sparse.density	Ratio of non-sparse points to total (dense) data points.


3.5
3.4
3.3
3.2
3.1
3.0
width
5.0
5.5
6.0
6.5
7.0
length


3.5
3.4
3.3
3.2
3.1
3.0
width
5.0
5.5
6.0
6.5
7.0
length
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
species

pandas.DataFrame.sparse.density

DataFrame.sparse.**density**
Ratio of non-sparse points to total (dense) data points.

DataFrame.sparse.from_spmatrix(data[, ...])	Create a new DataFrame from a scipy sparse matrix.
DataFrame.sparse.to_coo()	Return the contents of the frame as a sparse SciPy COO matrix.
DataFrame.sparse.to_dense()	Convert a DataFrame with sparse values to dense.

pandas.DataFrame.sparse.from_spmatrix

classmethod DataFrame.sparse.**from_spmatrix**(*data*, *index=None*, *columns=None*)
Create a new DataFrame from a scipy sparse matrix.

New in version 0.25.0.

Parameters

data [scipy.sparse.spmatrix] Must be convertible to csc format.

index, columns [Index, optional] Row and column labels to use for the resulting DataFrame. Defaults to a RangeIndex.

Returns

DataFrame Each column of the DataFrame is stored as a *arrays.SparseArray*.

Examples

```
>>> import scipy.sparse
>>> mat = scipy.sparse.eye(3)
>>> pd.DataFrame.sparse.from_spmatrix(mat)
     0    1    2
0  1.0  0.0  0.0
1  0.0  1.0  0.0
2  0.0  0.0  1.0
```

pandas.DataFrame.sparse.to_coo

DataFrame.sparse.**to_coo**()
Return the contents of the frame as a sparse SciPy COO matrix.

New in version 0.25.0.

Returns

coo_matrix [scipy.sparse.spmatrix] If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

Notes

The dtype will be the lowest-common-denominator type (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. By numpy.find_common_type convention, mixing int64 and and uint64 will result in a float64 dtype.

pandas.DataFrame.sparse.to_dense

`DataFrame.sparse.to_dense()`

Convert a DataFrame with sparse values to dense.

New in version 0.25.0.

Returns

DataFrame A DataFrame with the same values stored as dense arrays.

Examples

```
>>> df = pd.DataFrame({"A": pd.arrays.SparseArray([0, 1, 0])})
>>> df.sparse.to_dense()
   A
0  0
1  1
2  0
```

3.4.17 Serialization / IO / conversion

DataFrame.from_dict(data[, orient, dtype, ...])	Construct DataFrame from dict of array-like or dicts.
DataFrame.from_records(data[, index, ...])	Convert structured or record ndarray to DataFrame.
DataFrame.to_parquet([path, engine, ...])	Write a DataFrame to the binary parquet format.
DataFrame.to_pickle(path[, compression, ...])	Pickle (serialize) object to file.
DataFrame.to_csv([path_or_buf, sep, na_rep, ...])	Write object to a comma-separated values (csv) file.
DataFrame.to_hdf(path_or_buf, key[, mode, ...])	Write the contained data to an HDF5 file using HDFStore.
DataFrame.to_sql(name, con[, schema, ...])	Write records stored in a DataFrame to a SQL database.
DataFrame.to_dict([orient, into])	Convert the DataFrame to a dictionary.
DataFrame.to_excel(excel_writer[, ...])	Write object to an Excel sheet.
DataFrame.to_json([path_or_buf, orient, ...])	Convert the object to a JSON string.
DataFrame.to_html([buf, columns, col_space, ...])	Render a DataFrame as an HTML table.
DataFrame.to_feather(path, **kwargs)	Write a DataFrame to the binary Feather format.
DataFrame.to_latex([buf, columns, ...])	Render object to a LaTeX tabular, longtable, or nested table/tabular.
DataFrame.to_stata(path[, convert_dates, ...])	Export DataFrame object to Stata dta format.
DataFrame.to_gbq(destination_table[, ...])	Write a DataFrame to a Google BigQuery table.
DataFrame.to_records([index, column_dtypes, ...])	Convert DataFrame to a NumPy record array.

continues on next page

Table 80 – continued from previous page

`DataFrame.to_string`([buf, columns, ...])	Render a DataFrame to a console-friendly tabular output.
`DataFrame.to_clipboard`([excel, sep])	Copy object to the system clipboard.
`DataFrame.to_markdown`([buf, mode, index, ...])	Print DataFrame in Markdown-friendly format.
`DataFrame.style`	Returns a Styler object.

3.5 pandas arrays

For most data types, pandas uses NumPy arrays as the concrete objects contained with a `Index`, `Series`, or `DataFrame`.

For some data types, pandas extends NumPy's type system. String aliases for these types can be found at *dtypes*.

Kind of Data	pandas Data Type	Scalar	Array
TZ-aware datetime	`DatetimeTZDtype`	`Timestamp`	*Datetime data*
Timedeltas	(none)	`Timedelta`	*Timedelta data*
Period (time spans)	`PeriodDtype`	`Period`	*Timespan data*
Intervals	`IntervalDtype`	`Interval`	*Interval data*
Nullable Integer	`Int64Dtype`, ...	(none)	*Nullable integer*
Categorical	`CategoricalDtype`	(none)	*Categorical data*
Sparse	`SparseDtype`	(none)	*Sparse data*
Strings	`StringDtype`	`str`	*Text data*
Boolean (with NA)	`BooleanDtype`	`bool`	*Boolean data with missing values*

pandas and third-party libraries can extend NumPy's type system (see *Extension types*). The top-level `array()` method can be used to create a new array, which may be stored in a `Series`, `Index`, or as a column in a `DataFrame`.

`array`(data[, dtype, copy])	Create an array.

3.5.1 pandas.array

pandas.**array**(*data*, *dtype=None*, *copy=True*)

Create an array.

New in version 0.24.0.

Parameters

data [Sequence of objects] The scalars inside *data* should be instances of the scalar type for *dtype*. It's expected that *data* represents a 1-dimensional array of data.

When *data* is an Index or Series, the underlying array will be extracted from *data*.

dtype [str, np.dtype, or ExtensionDtype, optional] The dtype to use for the array. This may be a NumPy dtype or an extension type registered with pandas using `pandas.api.extensions.register_extension_dtype()`.

If not specified, there are two possibilities:

1. When *data* is a `Series`, `Index`, or `ExtensionArray`, the *dtype* will be taken from the data.

2. Otherwise, pandas will attempt to infer the *dtype* from the data.

Note that when *data* is a NumPy array, `data.dtype` is *not* used for inferring the array type. This is because NumPy cannot represent all the types of data that can be held in extension arrays.

Currently, pandas will infer an extension dtype for sequences of

Scalar Type	Array Type
pandas.Interval	*pandas.arrays.IntervalArray*
pandas.Period	*pandas.arrays.PeriodArray*
datetime.datetime	*pandas.arrays.DatetimeArray*
datetime.timedelta	*pandas.arrays.TimedeltaArray*
int	*pandas.arrays.IntegerArray*
float	pandas.arrays.FloatingArray
str	*pandas.arrays.StringArray*
bool	*pandas.arrays.BooleanArray*

For all other cases, NumPy's usual inference rules will be used.

Changed in version 1.0.0: Pandas infers nullable-integer dtype for integer data, string dtype for string data, and nullable-boolean dtype for boolean data.

Changed in version 1.2.0: Pandas now also infers nullable-floating dtype for float-like input data

copy [bool, default True] Whether to copy the data, even if not necessary. Depending on the type of *data*, creating the new array may require copying data, even if `copy=False`.

Returns

ExtensionArray The newly created array.

Raises

ValueError When *data* is not 1-dimensional.

See also:

numpy.array Construct a NumPy array.
Series Construct a pandas Series.
Index Construct a pandas Index.
arrays.PandasArray ExtensionArray wrapping a NumPy array.
Series.array Extract the array stored within a Series.

Notes

Omitting the *dtype* argument means pandas will attempt to infer the best array type from the values in the data. As new array types are added by pandas and 3rd party libraries, the "best" array type may change. We recommend specifying *dtype* to ensure that

1. the correct array type for the data is returned
2. the returned array type doesn't change as new extension types are added by pandas and third-party libraries

Additionally, if the underlying memory representation of the returned array matters, we recommend specifying the *dtype* as a concrete object rather than a string alias or allowing it to be inferred. For example, a future version of pandas or a 3rd-party library may include a dedicated ExtensionArray for string data. In this event, the following would no longer return a *arrays.PandasArray* backed by a NumPy array.

```
>>> pd.array(['a', 'b'], dtype=str)
<PandasArray>
['a', 'b']
Length: 2, dtype: str32
```

This would instead return the new ExtensionArray dedicated for string data. If you really need the new array to be backed by a NumPy array, specify that in the dtype.

```
>>> pd.array(['a', 'b'], dtype=np.dtype("<U1"))
<PandasArray>
['a', 'b']
Length: 2, dtype: str32
```

Finally, Pandas has arrays that mostly overlap with NumPy

- *arrays.DatetimeArray*
- *arrays.TimedeltaArray*

When data with a `datetime64[ns]` or `timedelta64[ns]` dtype is passed, pandas will always return a `DatetimeArray` or `TimedeltaArray` rather than a `PandasArray`. This is for symmetry with the case of timezone-aware data, which NumPy does not natively support.

```
>>> pd.array(['2015', '2016'], dtype='datetime64[ns]')
<DatetimeArray>
['2015-01-01 00:00:00', '2016-01-01 00:00:00']
Length: 2, dtype: datetime64[ns]
```

```
>>> pd.array(["1H", "2H"], dtype='timedelta64[ns]')
<TimedeltaArray>
['0 days 01:00:00', '0 days 02:00:00']
Length: 2, dtype: timedelta64[ns]
```

Examples

If a dtype is not specified, pandas will infer the best dtype from the values. See the description of *dtype* for the types pandas infers for.

```
>>> pd.array([1, 2])
<IntegerArray>
[1, 2]
Length: 2, dtype: Int64
```

```
>>> pd.array([1, 2, np.nan])
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

```
>>> pd.array([1.1, 2.2])
<FloatingArray>
[1.1, 2.2]
Length: 2, dtype: Float64
```

```
>>> pd.array(["a", None, "c"])
<StringArray>
['a', <NA>, 'c']
Length: 3, dtype: string
```

```
>>> pd.array([pd.Period('2000', freq="D"), pd.Period("2000", freq="D")])
<PeriodArray>
['2000-01-01', '2000-01-01']
Length: 2, dtype: period[D]
```

You can use the string alias for *dtype*

```
>>> pd.array(['a', 'b', 'a'], dtype='category')
['a', 'b', 'a']
Categories (2, object): ['a', 'b']
```

Or specify the actual dtype

```
>>> pd.array(['a', 'b', 'a'],
...          dtype=pd.CategoricalDtype(['a', 'b', 'c'], ordered=True))
['a', 'b', 'a']
Categories (3, object): ['a' < 'b' < 'c']
```

If pandas does not infer a dedicated extension type a *arrays.PandasArray* is returned.

```
>>> pd.array([1 + 1j, 3 + 2j])
<PandasArray>
[(1+1j), (3+2j)]
Length: 2, dtype: complex128
```

As mentioned in the "Notes" section, new extension types may be added in the future (by pandas or 3rd party libraries), causing the return value to no longer be a *arrays.PandasArray*. Specify the *dtype* as a NumPy dtype if you need to ensure there's no future change in behavior.

```
>>> pd.array([1, 2], dtype=np.dtype("int32"))
<PandasArray>
[1, 2]
Length: 2, dtype: int32
```

data must be 1-dimensional. A ValueError is raised when the input has the wrong dimensionality.

```
>>> pd.array(1)
Traceback (most recent call last):
  ...
ValueError: Cannot pass scalar '1' to 'pandas.array'.
```

3.5.2 Datetime data

NumPy cannot natively represent timezone-aware datetimes. pandas supports this with the *arrays.DatetimeArray* extension array, which can hold timezone-naive or timezone-aware values.

Timestamp, a subclass of datetime.datetime, is pandas' scalar type for timezone-naive or timezone-aware datetime data.

Timestamp([ts_input, freq, tz, unit, year, ...])	Pandas replacement for python datetime.datetime object.

pandas.Timestamp

class pandas.**Timestamp**(*ts_input=<object object>*, *freq=None*, *tz=None*, *unit=None*, *year=None*, *month=None*, *day=None*, *hour=None*, *minute=None*, *second=None*, *microsecond=None*, *nanosecond=None*, *tzinfo=None*, ***, *fold=None*)

Pandas replacement for python datetime.datetime object.

Timestamp is the pandas equivalent of python's Datetime and is interchangeable with it in most cases. It's the type used for the entries that make up a DatetimeIndex, and other timeseries oriented data structures in pandas.

Parameters

ts_input [datetime-like, str, int, float] Value to be converted to Timestamp.

freq [str, DateOffset] Offset which Timestamp will have.

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will have.

unit [str] Unit used for conversion if ts_input is of type int or float. The valid values are 'D', 'h', 'm', 's', 'ms', 'us', and 'ns'. For example, 's' means seconds and 'ms' means milliseconds.

year, month, day [int]

hour, minute, second, microsecond [int, optional, default 0]

nanosecond [int, optional, default 0]

tzinfo [datetime.tzinfo, optional, default None]

fold [{0, 1}, default None, keyword-only] Due to daylight saving time, one wall clock time can occur twice when shifting from summer to winter time; fold describes whether the datetime-like corresponds to the first (0) or the second time (1) the wall clock hits the ambiguous time

New in version 1.1.0.

Notes

There are essentially three calling conventions for the constructor. The primary form accepts four parameters. They can be passed by position or keyword.

The other two forms mimic the parameters from `datetime.datetime`. They can be passed by either position or keyword, but not both mixed together.

Examples

Using the primary calling convention:

This converts a datetime-like string

```
>>> pd.Timestamp('2017-01-01T12')
Timestamp('2017-01-01 12:00:00')
```

This converts a float representing a Unix epoch in units of seconds

```
>>> pd.Timestamp(1513393355.5, unit='s')
Timestamp('2017-12-16 03:02:35.500000')
```

This converts an int representing a Unix-epoch in units of seconds and for a particular timezone

```
>>> pd.Timestamp(1513393355, unit='s', tz='US/Pacific')
Timestamp('2017-12-15 19:02:35-0800', tz='US/Pacific')
```

Using the other two forms that mimic the API for `datetime.datetime`:

```
>>> pd.Timestamp(2017, 1, 1, 12)
Timestamp('2017-01-01 12:00:00')
```

```
>>> pd.Timestamp(year=2017, month=1, day=1, hour=12)
Timestamp('2017-01-01 12:00:00')
```

Attributes

asm8	Return numpy datetime64 format in nanoseconds.
day_of_week	Return day of the week.
day_of_year	Return the day of the year.
dayofweek	Return day of the week.
dayofyear	Return the day of the year.
days_in_month	Return the number of days in the month.
daysinmonth	Return the number of days in the month.
freqstr	Return the total number of days in the month.
is_leap_year	Return True if year is a leap year.
is_month_end	Return True if date is last day of month.
is_month_start	Return True if date is first day of month.
is_quarter_end	Return True if date is last day of the quarter.
is_quarter_start	Return True if date is first day of the quarter.
is_year_end	Return True if date is last day of the year.
is_year_start	Return True if date is first day of the year.
quarter	Return the quarter of the year.
tz	Alias for tzinfo.
week	Return the week number of the year.
weekofyear	Return the week number of the year.

pandas.Timestamp.asm8

Timestamp.**asm8**
Return numpy datetime64 format in nanoseconds.

pandas.Timestamp.day_of_week

Timestamp.**day_of_week**
Return day of the week.

pandas.Timestamp.day_of_year

Timestamp.**day_of_year**
Return the day of the year.

pandas.Timestamp.dayofweek

Timestamp.**dayofweek**
Return day of the week.

pandas.Timestamp.dayofyear

Timestamp.**dayofyear**
Return the day of the year.

pandas.Timestamp.days_in_month

Timestamp.**days_in_month**
Return the number of days in the month.

pandas.Timestamp.daysinmonth

Timestamp.**daysinmonth**
Return the number of days in the month.

pandas.Timestamp.freqstr

property Timestamp.**freqstr**
Return the total number of days in the month.

pandas.Timestamp.is_leap_year

Timestamp.**is_leap_year**
Return True if year is a leap year.

pandas.Timestamp.is_month_end

Timestamp.**is_month_end**
Return True if date is last day of month.

pandas.Timestamp.is_month_start

Timestamp.**is_month_start**
Return True if date is first day of month.

pandas.Timestamp.is_quarter_end

Timestamp.**is_quarter_end**
Return True if date is last day of the quarter.

pandas.Timestamp.is_quarter_start

Timestamp.**is_quarter_start**
Return True if date is first day of the quarter.

pandas.Timestamp.is_year_end

Timestamp.**is_year_end**
Return True if date is last day of the year.

pandas.Timestamp.is_year_start

Timestamp.**is_year_start**
Return True if date is first day of the year.

pandas.Timestamp.quarter

Timestamp.**quarter**
Return the quarter of the year.

pandas.Timestamp.tz

property Timestamp.**tz**
Alias for tzinfo.

pandas.Timestamp.week

Timestamp.**week**
Return the week number of the year.

pandas.Timestamp.weekofyear

Timestamp.**weekofyear**
Return the week number of the year.

day	
fold	
freq	
hour	
microsecond	
minute	
month	
nanosecond	
second	
tzinfo	
value	
year	

Methods

astimezone(tz)	Convert tz-aware Timestamp to another time zone.
ceil(freq[, ambiguous, nonexistent])	Return a new Timestamp ceiled to this resolution.
combine(date, time)	Combine date, time into datetime with same date and time fields.
ctime	Return ctime() style string.
date	Return date object with same year, month and day.
day_name	Return the day name of the Timestamp with specified locale.
dst	Return self.tzinfo.dst(self).
floor(freq[, ambiguous, nonexistent])	Return a new Timestamp floored to this resolution.
fromisocalendar	int, int, int -> Construct a date from the ISO year, week number and weekday.
fromisoformat	string -> datetime from datetime.isoformat() output
fromordinal(ordinal[, freq, tz])	Passed an ordinal, translate and convert to a ts.
fromtimestamp(ts)	Transform timestamp[, tz] to tz's local time from POSIX timestamp.
isocalendar	Return a 3-tuple containing ISO year, week number, and weekday.
isoformat	[sep] -> string in ISO 8601 format, YYYY-MM-DDT[HH[:MM[:SS[.mmm[uuu]]]]][+HH:MM].
isoweekday	Return the day of the week represented by the date.
month_name	Return the month name of the Timestamp with specified locale.

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normalize	Normalize Timestamp to midnight, preserving tz information.
now([tz])	Return new Timestamp object representing current time local to tz.
replace([year, month, day, hour, minute, ...])	Implements datetime.replace, handles nanoseconds.
round(freq[, ambiguous, nonexistent])	Round the Timestamp to the specified resolution.
strftime(format)	Return a string representing the given POSIX timestamp controlled by an explicit format string.
strptime(string, format)	Function is not implemented.
time	Return time object with same time but with tzinfo=None.
timestamp	Return POSIX timestamp as float.
timetuple	Return time tuple, compatible with time.localtime().
timetz	Return time object with same time and tzinfo.
to_datetime64	Return a numpy.datetime64 object with 'ns' precision.
to_julian_date()	Convert TimeStamp to a Julian Date.
to_numpy	Convert the Timestamp to a NumPy datetime64.
to_period	Return an period of which this timestamp is an observation.
to_pydatetime	Convert a Timestamp object to a native Python datetime object.
today(cls[, tz])	Return the current time in the local timezone.
toordinal	Return proleptic Gregorian ordinal.
tz_convert(tz)	Convert tz-aware Timestamp to another time zone.
tz_localize(tz[, ambiguous, nonexistent])	Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.
tzname	Return self.tzinfo.tzname(self).
utcfromtimestamp(ts)	Construct a naive UTC datetime from a POSIX timestamp.
utcnow()	Return a new Timestamp representing UTC day and time.
utcoffset	Return self.tzinfo.utcoffset(self).
utctimetuple	Return UTC time tuple, compatible with time.localtime().
weekday	Return the day of the week represented by the date.

pandas.Timestamp.astimezone

Timestamp.**astimezone**(*tz*)

Convert tz-aware Timestamp to another time zone.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will be converted to. None will remove timezone holding UTC time.

Returns

converted [Timestamp]

Raises

TypeError If Timestamp is tz-naive.

pandas.Timestamp.ceil

Timestamp.**ceil**(*freq*, *ambiguous='raise'*, *nonexistent='raise'*)

Return a new Timestamp ceiled to this resolution.

Parameters

freq [str] Frequency string indicating the ceiling resolution.

ambiguous [bool or {'raise', 'NaT'}, default 'raise'] The behavior is as follows:

- bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- 'NaT' will return NaT for an ambiguous time.
- 'raise' will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.

nonexistent [{'raise', 'shift_forward', 'shift_backward, 'NaT', timedelta}, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time.
- 'shift_backward' will shift the nonexistent time backward to the closest existing time.
- 'NaT' will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Raises

ValueError if the freq cannot be converted.

pandas.Timestamp.combine

classmethod Timestamp.**combine**(*date*, *time*)

Combine date, time into datetime with same date and time fields.

pandas.Timestamp.ctime

Timestamp.**ctime**()

Return ctime() style string.

pandas.Timestamp.date

Timestamp.**date**()
Return date object with same year, month and day.

pandas.Timestamp.day_name

Timestamp.**day_name**()
Return the day name of the Timestamp with specified locale.

Parameters

locale [str, default None (English locale)] Locale determining the language in which to return the day name.

Returns

str

pandas.Timestamp.dst

Timestamp.**dst**()
Return self.tzinfo.dst(self).

pandas.Timestamp.floor

Timestamp.**floor**(*freq*, *ambiguous='raise'*, *nonexistent='raise'*)
Return a new Timestamp floored to this resolution.

Parameters

freq [str] Frequency string indicating the flooring resolution.

ambiguous [bool or {'raise', 'NaT'}, default 'raise'] The behavior is as follows:

- bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- 'NaT' will return NaT for an ambiguous time.
- 'raise' will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.

nonexistent [{'raise', 'shift_forward', 'shift_backward, 'NaT', timedelta}, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time.
- 'shift_backward' will shift the nonexistent time backward to the closest existing time.
- 'NaT' will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Raises

ValueError if the freq cannot be converted.

pandas.Timestamp.fromisocalendar

`Timestamp.`**`fromisocalendar`**`()`

int, int, int -> Construct a date from the ISO year, week number and weekday.

This is the inverse of the date.isocalendar() function

pandas.Timestamp.fromisoformat

`Timestamp.`**`fromisoformat`**`()`

string -> datetime from datetime.isoformat() output

pandas.Timestamp.fromordinal

`classmethod` `Timestamp.`**`fromordinal`**`(`*ordinal*, *freq=None*, *tz=None*`)`

Passed an ordinal, translate and convert to a ts. Note: by definition there cannot be any tz info on the ordinal itself.

Parameters

ordinal [int] Date corresponding to a proleptic Gregorian ordinal.

freq [str, DateOffset] Offset to apply to the Timestamp.

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for the Timestamp.

pandas.Timestamp.fromtimestamp

`classmethod` `Timestamp.`**`fromtimestamp`**`(`*ts*`)`

Transform timestamp[, tz] to tz's local time from POSIX timestamp.

pandas.Timestamp.isocalendar

`Timestamp.`**`isocalendar`**`()`

Return a 3-tuple containing ISO year, week number, and weekday.

pandas.Timestamp.isoformat

`Timestamp.`**`isoformat`**`()`

[sep] -> string in ISO 8601 format, YYYY-MM-DDT[HH[:MM[:SS[.mmm[uuu]]]]][+HH:MM]. sep is used to separate the year from the time, and defaults to 'T'. timespec specifies what components of the time to include (allowed values are 'auto', 'hours', 'minutes', 'seconds', 'milliseconds', and 'microseconds').

pandas.Timestamp.isoweekday

Timestamp.**isoweekday**()
Return the day of the week represented by the date. Monday == 1 . . . Sunday == 7

pandas.Timestamp.month_name

Timestamp.**month_name**()
Return the month name of the Timestamp with specified locale.

Parameters

locale [str, default None (English locale)] Locale determining the language in which to return the month name.

Returns

str

pandas.Timestamp.normalize

Timestamp.**normalize**()
Normalize Timestamp to midnight, preserving tz information.

pandas.Timestamp.now

classmethod Timestamp.**now**(*tz=None*)
Return new Timestamp object representing current time local to tz.

Parameters

tz [str or timezone object, default None] Timezone to localize to.

pandas.Timestamp.replace

Timestamp.**replace**(*year=None*, *month=None*, *day=None*, *hour=None*, *minute=None*, *second=None*, *microsecond=None*, *nanosecond=None*, *tzinfo=<class 'object'>*, *fold=None*)
Implements datetime.replace, handles nanoseconds.

Parameters

year [int, optional]

month [int, optional]

day [int, optional]

hour [int, optional]

minute [int, optional]

second [int, optional]

microsecond [int, optional]

nanosecond [int, optional]

tzinfo [tz-convertible, optional]

fold [int, optional]

Returns

Timestamp with fields replaced

pandas.Timestamp.round

Timestamp.**round**(*freq*, *ambiguous='raise'*, *nonexistent='raise'*)

Round the Timestamp to the specified resolution.

Parameters

freq [str] Frequency string indicating the rounding resolution.

ambiguous [bool or {'raise', 'NaT'}, default 'raise'] The behavior is as follows:

- bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- 'NaT' will return NaT for an ambiguous time.
- 'raise' will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.

nonexistent [{'raise', 'shift_forward', 'shift_backward, 'NaT', timedelta}, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time.
- 'shift_backward' will shift the nonexistent time backward to the closest existing time.
- 'NaT' will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

a new Timestamp rounded to the given resolution of *freq*

Raises

ValueError if the freq cannot be converted

pandas.Timestamp.strftime

Timestamp.**strftime**(*format*)

Return a string representing the given POSIX timestamp controlled by an explicit format string.

Parameters

format [str] Format string to convert Timestamp to string. See strftime documentation for more information on the format string: https://docs.python.org/3/library/datetime.html#strftime-and-strptime-behavior.

pandas.Timestamp.strptime

classmethod Timestamp.**strptime**(*string*, *format*)

Function is not implemented. Use pd.to_datetime().

pandas.Timestamp.time

Timestamp.**time**()

Return time object with same time but with tzinfo=None.

pandas.Timestamp.timestamp

Timestamp.**timestamp**()

Return POSIX timestamp as float.

pandas.Timestamp.timetuple

Timestamp.**timetuple**()

Return time tuple, compatible with time.localtime().

pandas.Timestamp.timetz

Timestamp.**timetz**()

Return time object with same time and tzinfo.

pandas.Timestamp.to_datetime64

Timestamp.**to_datetime64**()

Return a numpy.datetime64 object with 'ns' precision.

pandas.Timestamp.to_julian_date

Timestamp.**to_julian_date**()
Convert TimeStamp to a Julian Date. 0 Julian date is noon January 1, 4713 BC.

pandas.Timestamp.to_numpy

Timestamp.**to_numpy**()
Convert the Timestamp to a NumPy datetime64.

New in version 0.25.0.

This is an alias method for *Timestamp.to_datetime64()*. The dtype and copy parameters are available here only for compatibility. Their values will not affect the return value.

Returns

numpy.datetime64

See also:

DatetimeIndex.to_numpy Similar method for DatetimeIndex.

pandas.Timestamp.to_period

Timestamp.**to_period**()
Return an period of which this timestamp is an observation.

pandas.Timestamp.to_pydatetime

Timestamp.**to_pydatetime**()
Convert a Timestamp object to a native Python datetime object.

If warn=True, issue a warning if nanoseconds is nonzero.

pandas.Timestamp.today

classmethod Timestamp.**today**(*cls*, *tz=None*)
Return the current time in the local timezone. This differs from datetime.today() in that it can be localized to a passed timezone.

Parameters

tz [str or timezone object, default None] Timezone to localize to.

pandas.Timestamp.toordinal

Timestamp.**toordinal**()
Return proleptic Gregorian ordinal. January 1 of year 1 is day 1.

pandas.Timestamp.tz_convert

Timestamp.**tz_convert**(*tz*)
Convert tz-aware Timestamp to another time zone.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will be converted to. None will remove timezone holding UTC time.

Returns

converted [Timestamp]

Raises

TypeError If Timestamp is tz-naive.

pandas.Timestamp.tz_localize

Timestamp.**tz_localize**(*tz*, *ambiguous='raise'*, *nonexistent='raise'*)
Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will be converted to. None will remove timezone holding local time.

ambiguous [bool, 'NaT', default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

The behavior is as follows:

- bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- 'NaT' will return NaT for an ambiguous time.
- 'raise' will raise an AmbiguousTimeError for an ambiguous time.

nonexistent ['shift_forward', 'shift_backward, 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

The behavior is as follows:

- 'shift_forward' will shift the nonexistent time forward to the closest existing time.
- 'shift_backward' will shift the nonexistent time backward to the closest existing time.
- 'NaT' will return NaT where there are nonexistent times.

- timedelta objects will shift nonexistent times by the timedelta.
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

localized [Timestamp]

Raises

TypeError If the Timestamp is tz-aware and tz is not None.

pandas.Timestamp.tzname

`Timestamp.`**`tzname`**`()`
Return self.tzinfo.tzname(self).

pandas.Timestamp.utcfromtimestamp

`classmethod` `Timestamp.`**`utcfromtimestamp`**`(`*`ts`*`)`
Construct a naive UTC datetime from a POSIX timestamp.

pandas.Timestamp.utcnow

`classmethod` `Timestamp.`**`utcnow`**`()`
Return a new Timestamp representing UTC day and time.

pandas.Timestamp.utcoffset

`Timestamp.`**`utcoffset`**`()`
Return self.tzinfo.utcoffset(self).

pandas.Timestamp.utctimetuple

`Timestamp.`**`utctimetuple`**`()`
Return UTC time tuple, compatible with time.localtime().

pandas.Timestamp.weekday

`Timestamp.`**`weekday`**`()`
Return the day of the week represented by the date. Monday == 0 . . . Sunday == 6

Properties

Timestamp.asm8	Return numpy datetime64 format in nanoseconds.
Timestamp.day	
Timestamp.dayofweek	Return day of the week.
Timestamp.day_of_week	Return day of the week.
Timestamp.dayofyear	Return the day of the year.
Timestamp.day_of_year	Return the day of the year.
Timestamp.days_in_month	Return the number of days in the month.
Timestamp.daysinmonth	Return the number of days in the month.
Timestamp.fold	
Timestamp.hour	
Timestamp.is_leap_year	Return True if year is a leap year.
Timestamp.is_month_end	Return True if date is last day of month.
Timestamp.is_month_start	Return True if date is first day of month.
Timestamp.is_quarter_end	Return True if date is last day of the quarter.
Timestamp.is_quarter_start	Return True if date is first day of the quarter.
Timestamp.is_year_end	Return True if date is last day of the year.
Timestamp.is_year_start	Return True if date is first day of the year.
Timestamp.max	
Timestamp.microsecond	
Timestamp.min	
Timestamp.minute	
Timestamp.month	
Timestamp.nanosecond	
Timestamp.quarter	Return the quarter of the year.
Timestamp.resolution	
Timestamp.second	
Timestamp.tz	Alias for tzinfo.
Timestamp.tzinfo	
Timestamp.value	
Timestamp.week	Return the week number of the year.
Timestamp.weekofyear	Return the week number of the year.
Timestamp.year	

pandas.Timestamp.day

Timestamp.**day**

pandas.Timestamp.fold

Timestamp.**fold**

pandas.Timestamp.hour

Timestamp.**hour**

pandas.Timestamp.max

Timestamp.**max = Timestamp('2262-04-11 23:47:16.854775807')**

pandas.Timestamp.microsecond

Timestamp.**microsecond**

pandas.Timestamp.min

Timestamp.**min = Timestamp('1677-09-21 00:12:43.145225')**

pandas.Timestamp.minute

Timestamp.**minute**

pandas.Timestamp.month

Timestamp.**month**

pandas.Timestamp.nanosecond

Timestamp.**nanosecond**

pandas.Timestamp.resolution

Timestamp.**resolution = Timedelta('0 days 00:00:00.000000001')**

pandas.Timestamp.second

Timestamp.**second**

pandas.Timestamp.tzinfo

Timestamp.**tzinfo**

pandas.Timestamp.value

Timestamp.**value**

pandas.Timestamp.year

Timestamp.**year**

Methods

Timestamp.astimezone(tz)	Convert tz-aware Timestamp to another time zone.
Timestamp.ceil(freq[, ambiguous, nonexistent])	Return a new Timestamp ceiled to this resolution.
Timestamp.combine(date, time)	Combine date, time into datetime with same date and time fields.
Timestamp.ctime	Return ctime() style string.
Timestamp.date	Return date object with same year, month and day.
Timestamp.day_name	Return the day name of the Timestamp with specified locale.
Timestamp.dst	Return self.tzinfo.dst(self).
Timestamp.floor(freq[, ambiguous, nonexistent])	Return a new Timestamp floored to this resolution.
Timestamp.freq	
Timestamp.freqstr	Return the total number of days in the month.
Timestamp.fromordinal(ordinal[, freq, tz])	Passed an ordinal, translate and convert to a ts.
Timestamp.fromtimestamp(ts)	Transform timestamp[, tz] to tz's local time from POSIX timestamp.
Timestamp.isocalendar	Return a 3-tuple containing ISO year, week number, and weekday.
Timestamp.isoformat	[sep] -> string in ISO 8601 format, YYYY-MM-DDT[HH[:MM[:SS[.mmm[uuu]]]]][+HH:MM].
Timestamp.isoweekday	Return the day of the week represented by the date.
Timestamp.month_name	Return the month name of the Timestamp with specified locale.
Timestamp.normalize	Normalize Timestamp to midnight, preserving tz information.
Timestamp.now([tz])	Return new Timestamp object representing current time local to tz.
Timestamp.replace([year, month, day, hour, ...])	Implements datetime.replace, handles nanoseconds.
Timestamp.round(freq[, ambiguous, nonexistent])	Round the Timestamp to the specified resolution.
Timestamp.strftime(format)	Return a string representing the given POSIX timestamp controlled by an explicit format string.

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Timestamp.strptime(string, format)	Function is not implemented.
Timestamp.time	Return time object with same time but with tzinfo=None.
Timestamp.timestamp	Return POSIX timestamp as float.
Timestamp.timetuple	Return time tuple, compatible with time.localtime().
Timestamp.timetz	Return time object with same time and tzinfo.
Timestamp.to_datetime64	Return a numpy.datetime64 object with 'ns' precision.
Timestamp.to_numpy	Convert the Timestamp to a NumPy datetime64.
Timestamp.to_julian_date()	Convert TimeStamp to a Julian Date.
Timestamp.to_period	Return an period of which this timestamp is an observation.
Timestamp.to_pydatetime	Convert a Timestamp object to a native Python datetime object.
Timestamp.today(cls[, tz])	Return the current time in the local timezone.
Timestamp.toordinal	Return proleptic Gregorian ordinal.
Timestamp.tz_convert(tz)	Convert tz-aware Timestamp to another time zone.
Timestamp.tz_localize(tz[, ambiguous, ...])	Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.
Timestamp.tzname	Return self.tzinfo.tzname(self).
Timestamp.utcfromtimestamp(ts)	Construct a naive UTC datetime from a POSIX timestamp.
Timestamp.utcnow()	Return a new Timestamp representing UTC day and time.
Timestamp.utcoffset	Return self.tzinfo.utcoffset(self).
Timestamp.utctimetuple	Return UTC time tuple, compatible with time.localtime().
Timestamp.weekday	Return the day of the week represented by the date.

pandas.Timestamp.freq

Timestamp.**freq**

A collection of timestamps may be stored in a *arrays.DatetimeArray*. For timezone-aware data, the `.dtype` of a `DatetimeArray` is a *DatetimeTZDtype*. For timezone-naive data, `np.dtype("datetime64[ns]")` is used.

If the data are tz-aware, then every value in the array must have the same timezone.

arrays.DatetimeArray(values[, dtype, freq, copy])	Pandas ExtensionArray for tz-naive or tz-aware datetime data.

pandas.arrays.DatetimeArray

class pandas.arrays.**DatetimeArray**(*values*, *dtype=dtype('<M8[ns]')*, *freq=None*, *copy=False*)

Pandas ExtensionArray for tz-naive or tz-aware datetime data.

New in version 0.24.0.

> **Warning:** DatetimeArray is currently experimental, and its API may change without warning. In particular, `DatetimeArray.dtype` is expected to change to always be an instance of an `ExtensionDtype`

subclass.

Parameters

values [Series, Index, DatetimeArray, ndarray] The datetime data.

For DatetimeArray *values* (or a Series or Index boxing one), *dtype* and *freq* will be extracted from *values*.

dtype [numpy.dtype or DatetimeTZDtype] Note that the only NumPy dtype allowed is 'datetime64[ns]'.

freq [str or Offset, optional] The frequency.

copy [bool, default False] Whether to copy the underlying array of values.

Attributes

None	

Methods

None	

DatetimeTZDtype([unit, tz])	An ExtensionDtype for timezone-aware datetime data.

pandas.DatetimeTZDtype

class pandas.**DatetimeTZDtype**(*unit='ns'*, *tz=None*)

An ExtensionDtype for timezone-aware datetime data.

This is not an actual numpy dtype, but a duck type.

Parameters

unit [str, default "ns"] The precision of the datetime data. Currently limited to `"ns"`.

tz [str, int, or datetime.tzinfo] The timezone.

Raises

pytz.UnknownTimeZoneError When the requested timezone cannot be found.

Examples

```
>>> pd.DatetimeTZDtype(tz='UTC')
datetime64[ns, UTC]
```

```
>>> pd.DatetimeTZDtype(tz='dateutil/US/Central')
datetime64[ns, tzfile('/usr/share/zoneinfo/US/Central')]
```

Attributes

unit	The precision of the datetime data.
tz	The timezone.

pandas.DatetimeTZDtype.unit

property DatetimeTZDtype.**unit**
The precision of the datetime data.

pandas.DatetimeTZDtype.tz

property DatetimeTZDtype.**tz**
The timezone.

Methods

None	

3.5.3 Timedelta data

NumPy can natively represent timedeltas. pandas provides *Timedelta* for symmetry with *Timestamp*.

Timedelta([value, unit])	Represents a duration, the difference between two dates or times.

pandas.Timedelta

class pandas.**Timedelta**(*value=<object object>*, *unit=None*, ***kwargs*)
Represents a duration, the difference between two dates or times.

Timedelta is the pandas equivalent of python's `datetime.timedelta` and is interchangeable with it in most cases.

Parameters

value [Timedelta, timedelta, np.timedelta64, str, or int]

unit [str, default 'ns'] Denote the unit of the input, if input is an integer.

Possible values:

- 'W', 'D', 'T', 'S', 'L', 'U', or 'N'
- 'days' or 'day'
- 'hours', 'hour', 'hr', or 'h'
- 'minutes', 'minute', 'min', or 'm'
- 'seconds', 'second', or 'sec'
- 'milliseconds', 'millisecond', 'millis', or 'milli'

- 'microseconds', 'microsecond', 'micros', or 'micro'
- 'nanoseconds', 'nanosecond', 'nanos', 'nano', or 'ns'.

****kwargs** Available kwargs: {days, seconds, microseconds, milliseconds, minutes, hours, weeks}. Values for construction in compat with datetime.timedelta. Numpy ints and floats will be coerced to python ints and floats.

Notes

The `.value` attribute is always in ns.

If the precision is higher than nanoseconds, the precision of the duration is truncated to nanoseconds.

Attributes

asm8	Return a numpy timedelta64 array scalar view.
components	Return a components namedtuple-like.
days	Number of days.
delta	Return the timedelta in nanoseconds (ns), for internal compatibility.
microseconds	Number of microseconds (>= 0 and less than 1 second).
nanoseconds	Return the number of nanoseconds (n), where 0 <= n < 1 microsecond.
resolution_string	Return a string representing the lowest timedelta resolution.
seconds	Number of seconds (>= 0 and less than 1 day).

pandas.Timedelta.asm8

Timedelta.**asm8**

Return a numpy timedelta64 array scalar view.

Provides access to the array scalar view (i.e. a combination of the value and the units) associated with the numpy.timedelta64().view(), including a 64-bit integer representation of the timedelta in nanoseconds (Python int compatible).

Returns

numpy timedelta64 array scalar view Array scalar view of the timedelta in nanoseconds.

Examples

```
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.asm8
numpy.timedelta64(86520000003042,'ns')
```

```
>>> td = pd.Timedelta('2 min 3 s')
>>> td.asm8
numpy.timedelta64(123000000000,'ns')
```

```
>>> td = pd.Timedelta('3 ms 5 us')
>>> td.asm8
numpy.timedelta64(3005000,'ns')
```

```
>>> td = pd.Timedelta(42, unit='ns')
>>> td.asm8
numpy.timedelta64(42,'ns')
```

pandas.Timedelta.components

Timedelta.**components**
Return a components namedtuple-like.

pandas.Timedelta.days

Timedelta.**days**
Number of days.

pandas.Timedelta.delta

Timedelta.**delta**
Return the timedelta in nanoseconds (ns), for internal compatibility.

Returns

int Timedelta in nanoseconds.

Examples

```
>>> td = pd.Timedelta('1 days 42 ns')
>>> td.delta
86400000000042
```

```
>>> td = pd.Timedelta('3 s')
>>> td.delta
3000000000
```

```
>>> td = pd.Timedelta('3 ms 5 us')
>>> td.delta
3005000
```

```
>>> td = pd.Timedelta(42, unit='ns')
>>> td.delta
42
```

pandas.Timedelta.microseconds

Timedelta.**microseconds**
Number of microseconds (>= 0 and less than 1 second).

pandas.Timedelta.nanoseconds

Timedelta.**nanoseconds**
Return the number of nanoseconds (n), where 0 <= n < 1 microsecond.

Returns

int Number of nanoseconds.

See also:

Timedelta.components Return all attributes with assigned values (i.e. days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds).

Examples

Using string input

```
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
```

```
>>> td.nanoseconds
42
```

Using integer input

```
>>> td = pd.Timedelta(42, unit='ns')
>>> td.nanoseconds
42
```

pandas.Timedelta.resolution_string

Timedelta.**resolution_string**
Return a string representing the lowest timedelta resolution.

Each timedelta has a defined resolution that represents the lowest OR most granular level of precision. Each level of resolution is represented by a short string as defined below:

Resolution: Return value

- Days: 'D'
- Hours: 'H'
- Minutes: 'T'

- Seconds: 'S'
- Milliseconds: 'L'
- Microseconds: 'U'
- Nanoseconds: 'N'

Returns

str Timedelta resolution.

Examples

```
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.resolution_string
'N'
```

```
>>> td = pd.Timedelta('1 days 2 min 3 us')
>>> td.resolution_string
'U'
```

```
>>> td = pd.Timedelta('2 min 3 s')
>>> td.resolution_string
'S'
```

```
>>> td = pd.Timedelta(36, unit='us')
>>> td.resolution_string
'U'
```

pandas.Timedelta.seconds

Timedelta.**seconds**
Number of seconds (>= 0 and less than 1 day).

freq	
is_populated	
value	

Methods

ceil(freq)	Return a new Timedelta ceiled to this resolution.
floor(freq)	Return a new Timedelta floored to this resolution.
isoformat	Format Timedelta as ISO 8601 Duration like `P[n]Y[n]M[n]DT[n]H[n]M[n]S`, where the `[n]` s are replaced by the values.
round(freq)	Round the Timedelta to the specified resolution.
to_numpy	Convert the Timedelta to a NumPy timedelta64.
to_pytimedelta	Convert a pandas Timedelta object into a python timedelta object.

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to_timedelta64	Return a numpy.timedelta64 object with 'ns' precision.
total_seconds	Total seconds in the duration.
view	Array view compatibility.

pandas.Timedelta.ceil

Timedelta.**ceil**(*freq*)

Return a new Timedelta ceiled to this resolution.

Parameters

freq [str] Frequency string indicating the ceiling resolution.

pandas.Timedelta.floor

Timedelta.**floor**(*freq*)

Return a new Timedelta floored to this resolution.

Parameters

freq [str] Frequency string indicating the flooring resolution.

pandas.Timedelta.isoformat

Timedelta.**isoformat**()

Format Timedelta as ISO 8601 Duration like `P[n]Y[n]M[n]DT[n]H[n]M[n]S`, where the `[n]` s are replaced by the values. See https://en.wikipedia.org/wiki/ISO_8601#Durations.

Returns

str

See also:

Timestamp.isoformat Function is used to convert the given Timestamp object into the ISO format.

Notes

The longest component is days, whose value may be larger than 365. Every component is always included, even if its value is 0. Pandas uses nanosecond precision, so up to 9 decimal places may be included in the seconds component. Trailing 0's are removed from the seconds component after the decimal. We do not 0 pad components, so it's . . . *T5H*. . . , not . . . *T05H*. . .

Examples

```
>>> td = pd.Timedelta(days=6, minutes=50, seconds=3,
...                   milliseconds=10, microseconds=10, nanoseconds=12)
```

```
>>> td.isoformat()
'P6DT0H50M3.010010012S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'P0DT0H0M10S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'P0DT0H0M10S'
>>> pd.Timedelta(days=500.5).isoformat()
'P500DT12H0MS'
```

pandas.Timedelta.round

Timedelta.**round**(*freq*)

Round the Timedelta to the specified resolution.

Parameters

freq [str] Frequency string indicating the rounding resolution.

Returns

a new Timedelta rounded to the given resolution of *freq*

Raises

ValueError if the freq cannot be converted

pandas.Timedelta.to_numpy

Timedelta.**to_numpy**()

Convert the Timedelta to a NumPy timedelta64.

New in version 0.25.0.

This is an alias method for *Timedelta.to_timedelta64()*. The dtype and copy parameters are available here only for compatibility. Their values will not affect the return value.

Returns

numpy.timedelta64

See also:

Series.to_numpy Similar method for Series.

pandas.Timedelta.to_pytimedelta

Timedelta.**to_pytimedelta**()
Convert a pandas Timedelta object into a python timedelta object.

Timedelta objects are internally saved as numpy datetime64[ns] dtype. Use to_pytimedelta() to convert to object dtype.

Returns

datetime.timedelta or numpy.array of datetime.timedelta

See also:

to_timedelta Convert argument to Timedelta type.

Notes

Any nanosecond resolution will be lost.

pandas.Timedelta.to_timedelta64

Timedelta.**to_timedelta64**()
Return a numpy.timedelta64 object with 'ns' precision.

pandas.Timedelta.total_seconds

Timedelta.**total_seconds**()
Total seconds in the duration.

pandas.Timedelta.view

Timedelta.**view**()
Array view compatibility.

Properties

Timedelta.asm8	Return a numpy timedelta64 array scalar view.
Timedelta.components	Return a components namedtuple-like.
Timedelta.days	Number of days.
Timedelta.delta	Return the timedelta in nanoseconds (ns), for internal compatibility.
Timedelta.freq	
Timedelta.is_populated	
Timedelta.max	
Timedelta.microseconds	Number of microseconds (>= 0 and less than 1 second).
Timedelta.min	
Timedelta.nanoseconds	Return the number of nanoseconds (n), where 0 <= n < 1 microsecond.

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Timedelta.resolution	
Timedelta.seconds	Number of seconds (>= 0 and less than 1 day).
Timedelta.value	
Timedelta.view	Array view compatibility.

pandas.Timedelta.freq

Timedelta.**freq**

pandas.Timedelta.is_populated

Timedelta.**is_populated**

pandas.Timedelta.max

Timedelta.**max = Timedelta('106751 days 23:47:16.854775807')**

pandas.Timedelta.min

Timedelta.**min = Timedelta('-106752 days +00:12:43.145224193')**

pandas.Timedelta.resolution

Timedelta.**resolution = Timedelta('0 days 00:00:00.000000001')**

pandas.Timedelta.value

Timedelta.**value**

Methods

Timedelta.ceil(freq)	Return a new Timedelta ceiled to this resolution.
Timedelta.floor(freq)	Return a new Timedelta floored to this resolution.
Timedelta.isoformat	Format Timedelta as ISO 8601 Duration like `P[n]Y[n]M[n]DT[n]H[n]M[n]S`, where the `[n]` s are replaced by the values.
Timedelta.round(freq)	Round the Timedelta to the specified resolution.
Timedelta.to_pytimedelta	Convert a pandas Timedelta object into a python timedelta object.
Timedelta.to_timedelta64	Return a numpy.timedelta64 object with 'ns' precision.
Timedelta.to_numpy	Convert the Timedelta to a NumPy timedelta64.
Timedelta.total_seconds	Total seconds in the duration.

A collection of timedeltas may be stored in a `TimedeltaArray`.

arrays.TimedeltaArray(values[, dtype, freq, ...])	Pandas ExtensionArray for timedelta data.

pandas.arrays.TimedeltaArray

class pandas.arrays.**TimedeltaArray**(*values*, *dtype=dtype('<m8[ns]')*, *freq=<object object>*, *copy=False*)

Pandas ExtensionArray for timedelta data.

New in version 0.24.0.

Warning: TimedeltaArray is currently experimental, and its API may change without warning. In particular, `TimedeltaArray.dtype` is expected to change to be an instance of an `ExtensionDtype` subclass.

Parameters

values [array-like] The timedelta data.

dtype [numpy.dtype] Currently, only `numpy.dtype("timedelta64[ns]")` is accepted.

freq [Offset, optional]

copy [bool, default False] Whether to copy the underlying array of data.

Attributes

None	

Methods

None	

3.5.4 Timespan data

pandas represents spans of times as *Period* objects.

3.5.5 Period

Period([value, freq, ordinal, year, month, ...])	Represents a period of time.

pandas.Period

class pandas.**Period**(*value=None*, *freq=None*, *ordinal=None*, *year=None*, *month=None*, *quarter=None*, *day=None*, *hour=None*, *minute=None*, *second=None*)

Represents a period of time.

Parameters

value [Period or str, default None] The time period represented (e.g., '4Q2005').

freq [str, default None] One of pandas period strings or corresponding objects.

ordinal [int, default None] The period offset from the proleptic Gregorian epoch.

year [int, default None] Year value of the period.

month [int, default 1] Month value of the period.

quarter [int, default None] Quarter value of the period.

day [int, default 1] Day value of the period.

hour [int, default 0] Hour value of the period.

minute [int, default 0] Minute value of the period.

second [int, default 0] Second value of the period.

Attributes

day	Get day of the month that a Period falls on.
day_of_week	Day of the week the period lies in, with Monday=0 and Sunday=6.
day_of_year	Return the day of the year.
dayofweek	Day of the week the period lies in, with Monday=0 and Sunday=6.
dayofyear	Return the day of the year.
days_in_month	Get the total number of days in the month that this period falls on.
daysinmonth	Get the total number of days of the month that the Period falls in.
hour	Get the hour of the day component of the Period.
minute	Get minute of the hour component of the Period.
qyear	Fiscal year the Period lies in according to its starting-quarter.
second	Get the second component of the Period.
start_time	Get the Timestamp for the start of the period.
week	Get the week of the year on the given Period.
weekday	Day of the week the period lies in, with Monday=0 and Sunday=6.

pandas.Period.day

Period.**day**

Get day of the month that a Period falls on.

Returns

int

See also:

Period.dayofweek Get the day of the week.

Period.dayofyear Get the day of the year.

Examples

```
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.day
11
```

pandas.Period.day_of_week

Period.**day_of_week**

Day of the week the period lies in, with Monday=0 and Sunday=6.

If the period frequency is lower than daily (e.g. hourly), and the period spans over multiple days, the day at the start of the period is used.

If the frequency is higher than daily (e.g. monthly), the last day of the period is used.

Returns

int Day of the week.

See also:

Period.day_of_week Day of the week the period lies in.

Period.weekday Alias of Period.day_of_week.

Period.day Day of the month.

Period.dayofyear Day of the year.

Examples

```
>>> per = pd.Period('2017-12-31 22:00', 'H')
>>> per.day_of_week
6
```

For periods that span over multiple days, the day at the beginning of the period is returned.

```
>>> per = pd.Period('2017-12-31 22:00', '4H')
>>> per.day_of_week
6
>>> per.start_time.day_of_week
6
```

For periods with a frequency higher than days, the last day of the period is returned.

```
>>> per = pd.Period('2018-01', 'M')
>>> per.day_of_week
2
>>> per.end_time.day_of_week
2
```

pandas.Period.day_of_year

Period.**day_of_year**

Return the day of the year.

This attribute returns the day of the year on which the particular date occurs. The return value ranges between 1 to 365 for regular years and 1 to 366 for leap years.

Returns

int The day of year.

See also:

Period.day Return the day of the month.

Period.day_of_week Return the day of week.

PeriodIndex.day_of_year Return the day of year of all indexes.

Examples

```
>>> period = pd.Period("2015-10-23", freq='H')
>>> period.day_of_year
296
>>> period = pd.Period("2012-12-31", freq='D')
>>> period.day_of_year
366
>>> period = pd.Period("2013-01-01", freq='D')
>>> period.day_of_year
1
```

pandas.Period.dayofweek

Period.**dayofweek**

Day of the week the period lies in, with Monday=0 and Sunday=6.

If the period frequency is lower than daily (e.g. hourly), and the period spans over multiple days, the day at the start of the period is used.

If the frequency is higher than daily (e.g. monthly), the last day of the period is used.

Returns

int Day of the week.

See also:

Period.day_of_week Day of the week the period lies in.

Period.weekday Alias of Period.day_of_week.

Period.day Day of the month.

Period.dayofyear Day of the year.

Examples

```
>>> per = pd.Period('2017-12-31 22:00', 'H')
>>> per.day_of_week
6
```

For periods that span over multiple days, the day at the beginning of the period is returned.

```
>>> per = pd.Period('2017-12-31 22:00', '4H')
>>> per.day_of_week
6
>>> per.start_time.day_of_week
6
```

For periods with a frequency higher than days, the last day of the period is returned.

```
>>> per = pd.Period('2018-01', 'M')
>>> per.day_of_week
2
>>> per.end_time.day_of_week
2
```

pandas.Period.dayofyear

Period.**dayofyear**

Return the day of the year.

This attribute returns the day of the year on which the particular date occurs. The return value ranges between 1 to 365 for regular years and 1 to 366 for leap years.

Returns

int The day of year.

See also:

Period.day Return the day of the month.

Period.day_of_week Return the day of week.

PeriodIndex.day_of_year Return the day of year of all indexes.

Examples

```
>>> period = pd.Period("2015-10-23", freq='H')
>>> period.day_of_year
296
>>> period = pd.Period("2012-12-31", freq='D')
>>> period.day_of_year
366
>>> period = pd.Period("2013-01-01", freq='D')
>>> period.day_of_year
1
```

pandas.Period.days_in_month

Period.**days_in_month**

Get the total number of days in the month that this period falls on.

Returns

int

See also:

Period.daysinmonth Gets the number of days in the month.

DatetimeIndex.daysinmonth Gets the number of days in the month.

calendar.monthrange Returns a tuple containing weekday (0-6 ~ Mon-Sun) and number of days (28-31).

Examples

```
>>> p = pd.Period('2018-2-17')
>>> p.days_in_month
28
```

```
>>> pd.Period('2018-03-01').days_in_month
31
```

Handles the leap year case as well:

```
>>> p = pd.Period('2016-2-17')
>>> p.days_in_month
29
```

pandas.Period.daysinmonth

Period.**daysinmonth**

Get the total number of days of the month that the Period falls in.

Returns

int

See also:

Period.days_in_month Return the days of the month.

Period.dayofyear Return the day of the year.

Examples

```
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.daysinmonth
31
```

pandas.Period.hour

Period.**hour**

Get the hour of the day component of the Period.

Returns

int The hour as an integer, between 0 and 23.

See also:

Period.second Get the second component of the Period.

Period.minute Get the minute component of the Period.

Examples

```
>>> p = pd.Period("2018-03-11 13:03:12.050000")
>>> p.hour
13
```

Period longer than a day

```
>>> p = pd.Period("2018-03-11", freq="M")
>>> p.hour
0
```

pandas.Period.minute

Period.**minute**

Get minute of the hour component of the Period.

Returns

int The minute as an integer, between 0 and 59.

See also:

Period.hour Get the hour component of the Period.

Period.second Get the second component of the Period.

Examples

```
>>> p = pd.Period("2018-03-11 13:03:12.050000")
>>> p.minute
3
```

pandas.Period.qyear

Period.**qyear**

Fiscal year the Period lies in according to its starting-quarter.

The *year* and the *qyear* of the period will be the same if the fiscal and calendar years are the same. When they are not, the fiscal year can be different from the calendar year of the period.

Returns

int The fiscal year of the period.

See also:

Period.year Return the calendar year of the period.

Examples

If the natural and fiscal year are the same, *qyear* and *year* will be the same.

```
>>> per = pd.Period('2018Q1', freq='Q')
>>> per.qyear
2018
>>> per.year
2018
```

If the fiscal year starts in April (*Q-MAR*), the first quarter of 2018 will start in April 2017. *year* will then be 2018, but *qyear* will be the fiscal year, 2018.

```
>>> per = pd.Period('2018Q1', freq='Q-MAR')
>>> per.start_time
Timestamp('2017-04-01 00:00:00')
>>> per.qyear
2018
```

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```
>>> per.year
2017
```

pandas.Period.second

Period.**second**

Get the second component of the Period.

Returns

int The second of the Period (ranges from 0 to 59).

See also:

Period.hour Get the hour component of the Period.

Period.minute Get the minute component of the Period.

Examples

```
>>> p = pd.Period("2018-03-11 13:03:12.050000")
>>> p.second
12
```

pandas.Period.start_time

Period.**start_time**

Get the Timestamp for the start of the period.

Returns

Timestamp

See also:

Period.end_time Return the end Timestamp.

Period.dayofyear Return the day of year.

Period.daysinmonth Return the days in that month.

Period.dayofweek Return the day of the week.

Examples

```
>>> period = pd.Period('2012-1-1', freq='D')
>>> period
Period('2012-01-01', 'D')
```

```
>>> period.start_time
Timestamp('2012-01-01 00:00:00')
```

```
>>> period.end_time
Timestamp('2012-01-01 23:59:59.999999999')
```

pandas.Period.week

Period.**week**

Get the week of the year on the given Period.

Returns

int

See also:

Period.dayofweek Get the day component of the Period.

Period.weekday Get the day component of the Period.

Examples

```
>>> p = pd.Period("2018-03-11", "H")
>>> p.week
10
```

```
>>> p = pd.Period("2018-02-01", "D")
>>> p.week
5
```

```
>>> p = pd.Period("2018-01-06", "D")
>>> p.week
1
```

pandas.Period.weekday

Period.**weekday**

Day of the week the period lies in, with Monday=0 and Sunday=6.

If the period frequency is lower than daily (e.g. hourly), and the period spans over multiple days, the day at the start of the period is used.

If the frequency is higher than daily (e.g. monthly), the last day of the period is used.

Returns

int Day of the week.

See also:

Period.dayofweek Day of the week the period lies in.

Period.weekday Alias of Period.dayofweek.

Period.day Day of the month.

Period.dayofyear Day of the year.

Examples

```
>>> per = pd.Period('2017-12-31 22:00', 'H')
>>> per.dayofweek
6
```

For periods that span over multiple days, the day at the beginning of the period is returned.

```
>>> per = pd.Period('2017-12-31 22:00', '4H')
>>> per.dayofweek
6
>>> per.start_time.dayofweek
6
```

For periods with a frequency higher than days, the last day of the period is returned.

```
>>> per = pd.Period('2018-01', 'M')
>>> per.dayofweek
2
>>> per.end_time.dayofweek
2
```

end_time	
freq	
freqstr	
is_leap_year	
month	
ordinal	
quarter	
weekofyear	
year	

Methods

asfreq	Convert Period to desired frequency, at the start or end of the interval.
strftime	Returns the string representation of the *Period*, depending on the selected `fmt`.
to_timestamp	Return the Timestamp representation of the Period.

pandas.Period.asfreq

`Period.`**`asfreq`**`()`

Convert Period to desired frequency, at the start or end of the interval.

Parameters

freq [str] The desired frequency.

how [{'E', 'S', 'end', 'start'}, default 'end'] Start or end of the timespan.

Returns

resampled [Period]

pandas.Period.strftime

Period.**strftime**()

Returns the string representation of the *Period*, depending on the selected `fmt`. `fmt` must be a string containing one or several directives. The method recognizes the same directives as the `time.strftime()` function of the standard Python distribution, as well as the specific additional directives `%f`, `%F`, `%q`. (formatting & docs originally from scikits.timeries).

Directive	Meaning	Notes
`%a`	Locale's abbreviated weekday name.	
`%A`	Locale's full weekday name.	
`%b`	Locale's abbreviated month name.	
`%B`	Locale's full month name.	
`%c`	Locale's appropriate date and time representation.	
`%d`	Day of the month as a decimal number [01,31].	
`%f`	'Fiscal' year without a century as a decimal number [00,99]	(1)
`%F`	'Fiscal' year with a century as a decimal number	(2)
`%H`	Hour (24-hour clock) as a decimal number [00,23].	
`%I`	Hour (12-hour clock) as a decimal number [01,12].	
`%j`	Day of the year as a decimal number [001,366].	
`%m`	Month as a decimal number [01,12].	
`%M`	Minute as a decimal number [00,59].	
`%p`	Locale's equivalent of either AM or PM.	(3)
`%q`	Quarter as a decimal number [01,04]	
`%S`	Second as a decimal number [00,61].	(4)
`%U`	Week number of the year (Sunday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Sunday are considered to be in week 0.	(5)
`%w`	Weekday as a decimal number [0(Sunday),6].	
`%W`	Week number of the year (Monday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Monday are considered to be in week 0.	(5)
`%x`	Locale's appropriate date representation.	
`%X`	Locale's appropriate time representation.	
`%y`	Year without century as a decimal number [00,99].	
`%Y`	Year with century as a decimal number.	
`%Z`	Time zone name (no characters if no time zone exists).	
`%%`	A literal `'%'` character.	

Notes

(1) The `%f` directive is the same as `%y` if the frequency is not quarterly. Otherwise, it corresponds to the 'fiscal' year, as defined by the *qyear* attribute.

(2) The `%F` directive is the same as `%Y` if the frequency is not quarterly. Otherwise, it corresponds to the 'fiscal' year, as defined by the *qyear* attribute.

(3) The `%p` directive only affects the output hour field if the `%I` directive is used to parse the hour.

(4) The range really is `0` to `61`; this accounts for leap seconds and the (very rare) double leap seconds.

(5) The `%U` and `%W` directives are only used in calculations when the day of the week and the year are specified.

Examples

```
>>> a = Period(freq='Q-JUL', year=2006, quarter=1)
>>> a.strftime('%F-Q%q')
'2006-Q1'
>>> # Output the last month in the quarter of this date
>>> a.strftime('%b-%Y')
'Oct-2005'
>>>
>>> a = Period(freq='D', year=2001, month=1, day=1)
>>> a.strftime('%d-%b-%Y')
'01-Jan-2006'
>>> a.strftime('%b. %d, %Y was a %A')
'Jan. 01, 2001 was a Monday'
```

pandas.Period.to_timestamp

Period.**to_timestamp**()

Return the Timestamp representation of the Period.

Uses the target frequency specified at the part of the period specified by *how*, which is either *Start* or *Finish*.

Parameters

freq [str or DateOffset] Target frequency. Default is 'D' if self.freq is week or longer and 'S' otherwise.

how [str, default 'S' (start)] One of 'S', 'E'. Can be aliased as case insensitive 'Start', 'Finish', 'Begin', 'End'.

Returns

Timestamp

now	

Properties

Period.day	Get day of the month that a Period falls on.
Period.dayofweek	Day of the week the period lies in, with Monday=0 and Sunday=6.
Period.day_of_week	Day of the week the period lies in, with Monday=0 and Sunday=6.
Period.dayofyear	Return the day of the year.
Period.day_of_year	Return the day of the year.
Period.days_in_month	Get the total number of days in the month that this period falls on.
Period.daysinmonth	Get the total number of days of the month that the Period falls in.
Period.end_time	
Period.freq	
Period.freqstr	
Period.hour	Get the hour of the day component of the Period.
Period.is_leap_year	
Period.minute	Get minute of the hour component of the Period.
Period.month	
Period.ordinal	
Period.quarter	
Period.qyear	Fiscal year the Period lies in according to its starting-quarter.
Period.second	Get the second component of the Period.
Period.start_time	Get the Timestamp for the start of the period.
Period.week	Get the week of the year on the given Period.
Period.weekday	Day of the week the period lies in, with Monday=0 and Sunday=6.
Period.weekofyear	
Period.year	

pandas.Period.end_time

Period.**end_time**

pandas.Period.freq

Period.**freq**

pandas.Period.freqstr

Period.**freqstr**

pandas.Period.is_leap_year

Period.**is_leap_year**

pandas.Period.month

Period.**month**

pandas.Period.ordinal

Period.**ordinal**

pandas.Period.quarter

Period.**quarter**

pandas.Period.weekofyear

Period.**weekofyear**

pandas.Period.year

Period.**year**

Methods

Period.asfreq	Convert Period to desired frequency, at the start or end of the interval.
Period.now	
Period.strftime	Returns the string representation of the *Period*, depending on the selected `fmt`.
Period.to_timestamp	Return the Timestamp representation of the Period.

pandas.Period.now

Period.**now**()

A collection of timedeltas may be stored in a *arrays.PeriodArray*. Every period in a PeriodArray must have the same freq.

arrays.PeriodArray(values[, dtype, freq, copy])	Pandas ExtensionArray for storing Period data.

pandas.arrays.PeriodArray

class pandas.arrays.**PeriodArray**(*values*, *dtype=None*, *freq=None*, *copy=False*)

Pandas ExtensionArray for storing Period data.

Users should use period_range() to create new instances. Alternatively, array() can be used to create new instances from a sequence of Period scalars.

Parameters

values [Union[PeriodArray, Series[period], ndarray[int], PeriodIndex]] The data to store. These should be arrays that can be directly converted to ordinals without inference or copy (PeriodArray, ndarray[int64]), or a box around such an array (Series[period], PeriodIndex).

dtype [PeriodDtype, optional] A PeriodDtype instance from which to extract a *freq*. If both *freq* and *dtype* are specified, then the frequencies must match.

freq [str or DateOffset] The *freq* to use for the array. Mostly applicable when *values* is an ndarray of integers, when *freq* is required. When *values* is a PeriodArray (or box around), it's checked that values.freq matches *freq*.

copy [bool, default False] Whether to copy the ordinals before storing.

See also:

Period Represents a period of time.
PeriodIndex Immutable Index for period data.
period_range Create a fixed-frequency PeriodArray.
array Construct a pandas array.

Notes

There are two components to a PeriodArray

- ordinals : integer ndarray
- freq : pd.tseries.offsets.Offset

The values are physically stored as a 1-D ndarray of integers. These are called "ordinals" and represent some kind of offset from a base.

The *freq* indicates the span covered by each element of the array. All elements in the PeriodArray have the same *freq*.

Attributes

None	

Methods

None	

PeriodDtype([freq])	An ExtensionDtype for Period data.

pandas.PeriodDtype

class pandas.**PeriodDtype**(*freq=None*)

An ExtensionDtype for Period data.

This is not an actual numpy dtype, but a duck type.

Parameters

freq [str or DateOffset] The frequency of this PeriodDtype.

Examples

```
>>> pd.PeriodDtype(freq='D')
period[D]
```

```
>>> pd.PeriodDtype(freq=pd.offsets.MonthEnd())
period[M]
```

Attributes

freq	The frequency object of this PeriodDtype.

pandas.PeriodDtype.freq

property PeriodDtype.**freq**

The frequency object of this PeriodDtype.

Methods

None	

3.5.6 Interval data

Arbitrary intervals can be represented as *Interval* objects.

Interval	Immutable object implementing an Interval, a bounded slice-like interval.

pandas.Interval

class pandas.**Interval**

Immutable object implementing an Interval, a bounded slice-like interval.

Parameters

left [orderable scalar] Left bound for the interval.

right [orderable scalar] Right bound for the interval.

closed [{'right', 'left', 'both', 'neither'}, default 'right'] Whether the interval is closed on the left-side, right-side, both or neither. See the Notes for more detailed explanation.

See also:

IntervalIndex An Index of Interval objects that are all closed on the same side.
cut Convert continuous data into discrete bins (Categorical of Interval objects).
qcut Convert continuous data into bins (Categorical of Interval objects) based on quantiles.
Period Represents a period of time.

Notes

The parameters *left* and *right* must be from the same type, you must be able to compare them and they must satisfy `left <= right`.

A closed interval (in mathematics denoted by square brackets) contains its endpoints, i.e. the closed interval `[0, 5]` is characterized by the conditions `0 <= x <= 5`. This is what `closed='both'` stands for. An open interval (in mathematics denoted by parentheses) does not contain its endpoints, i.e. the open interval `(0, 5)` is characterized by the conditions `0 < x < 5`. This is what `closed='neither'` stands for. Intervals can also be half-open or half-closed, i.e. `[0, 5)` is described by `0 <= x < 5` (`closed='left'`) and `(0, 5]` is described by `0 < x <= 5` (`closed='right'`).

Examples

It is possible to build Intervals of different types, like numeric ones:

```
>>> iv = pd.Interval(left=0, right=5)
>>> iv
Interval(0, 5, closed='right')
```

You can check if an element belongs to it

```
>>> 2.5 in iv
True
```

You can test the bounds (`closed='right'`, so `0 < x <= 5`):

```
>>> 0 in iv
False
>>> 5 in iv
True
>>> 0.0001 in iv
True
```

Calculate its length

```
>>> iv.length
5
```

You can operate with + and * over an Interval and the operation is applied to each of its bounds, so the result depends on the type of the bound elements

```
>>> shifted_iv = iv + 3
>>> shifted_iv
Interval(3, 8, closed='right')
>>> extended_iv = iv * 10.0
>>> extended_iv
Interval(0.0, 50.0, closed='right')
```

To create a time interval you can use Timestamps as the bounds

```
>>> year_2017 = pd.Interval(pd.Timestamp('2017-01-01 00:00:00'),
...                         pd.Timestamp('2018-01-01 00:00:00'),
...                         closed='left')
>>> pd.Timestamp('2017-01-01 00:00') in year_2017
True
>>> year_2017.length
Timedelta('365 days 00:00:00')
```

Attributes

closed	Whether the interval is closed on the left-side, right-side, both or neither.
closed_left	Check if the interval is closed on the left side.
closed_right	Check if the interval is closed on the right side.
is_empty	Indicates if an interval is empty, meaning it contains no points.
left	Left bound for the interval.
length	Return the length of the Interval.
mid	Return the midpoint of the Interval.
open_left	Check if the interval is open on the left side.
open_right	Check if the interval is open on the right side.
right	Right bound for the interval.

pandas.Interval.closed

Interval.**closed**
Whether the interval is closed on the left-side, right-side, both or neither.

pandas.Interval.closed_left

Interval.**closed_left**
Check if the interval is closed on the left side.

For the meaning of *closed* and *open* see *Interval*.

Returns

bool True if the Interval is closed on the left-side.

pandas.Interval.closed_right

Interval.**closed_right**
Check if the interval is closed on the right side.

For the meaning of *closed* and *open* see *Interval*.

Returns

bool True if the Interval is closed on the left-side.

pandas.Interval.is_empty

Interval.**is_empty**
Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

Returns

bool or ndarray A boolean indicating if a scalar *Interval* is empty, or a boolean ndarray positionally indicating if an Interval in an *IntervalArray* or *IntervalIndex* is empty.

Examples

An *Interval* that contains points is not empty:

```
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An Interval that does not contain any points is empty:

```
>>> pd.Interval(0, 0, closed='right').is_empty
True
>>> pd.Interval(0, 0, closed='left').is_empty
True
>>> pd.Interval(0, 0, closed='neither').is_empty
True
```

An Interval that contains a single point is not empty:

```
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An *IntervalArray* or *IntervalIndex* returns a boolean ndarray positionally indicating if an Interval is empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'),
...        pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

pandas.Interval.left

Interval.**left**
Left bound for the interval.

pandas.Interval.length

Interval.**length**
Return the length of the Interval.

pandas.Interval.mid

Interval.**mid**
Return the midpoint of the Interval.

pandas.Interval.open_left

Interval.**open_left**
Check if the interval is open on the left side.

For the meaning of *closed* and *open* see *Interval*.

Returns

bool True if the Interval is closed on the left-side.

pandas.Interval.open_right

Interval.**open_right**
Check if the interval is open on the right side.

For the meaning of *closed* and *open* see *Interval*.

Returns

bool True if the Interval is closed on the left-side.

pandas.Interval.right

Interval.**right**
Right bound for the interval.

Methods

overlaps	Check whether two Interval objects overlap.

pandas.Interval.overlaps

Interval.**overlaps**()
Check whether two Interval objects overlap.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

Parameters

other [Interval] Interval to check against for an overlap.

Returns

bool True if the two intervals overlap.

See also:

`IntervalArray.overlaps` The corresponding method for IntervalArray.

`IntervalIndex.overlaps` The corresponding method for IntervalIndex.

Examples

```
>>> i1 = pd.Interval(0, 2)
>>> i2 = pd.Interval(1, 3)
>>> i1.overlaps(i2)
True
>>> i3 = pd.Interval(4, 5)
>>> i1.overlaps(i3)
False
```

Intervals that share closed endpoints overlap:

```
>>> i4 = pd.Interval(0, 1, closed='both')
>>> i5 = pd.Interval(1, 2, closed='both')
>>> i4.overlaps(i5)
True
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> i6 = pd.Interval(1, 2, closed='neither')
>>> i4.overlaps(i6)
False
```

Properties

Interval.closed	Whether the interval is closed on the left-side, right-side, both or neither.
Interval.closed_left	Check if the interval is closed on the left side.
Interval.closed_right	Check if the interval is closed on the right side.
Interval.is_empty	Indicates if an interval is empty, meaning it contains no points.
Interval.left	Left bound for the interval.
Interval.length	Return the length of the Interval.
Interval.mid	Return the midpoint of the Interval.
Interval.open_left	Check if the interval is open on the left side.
Interval.open_right	Check if the interval is open on the right side.
Interval.overlaps	Check whether two Interval objects overlap.
Interval.right	Right bound for the interval.

A collection of intervals may be stored in an *arrays.IntervalArray*.

arrays.IntervalArray(data[, closed, dtype, ...])	Pandas array for interval data that are closed on the same side.

pandas.arrays.IntervalArray

class pandas.arrays.**IntervalArray**(*data*, *closed=None*, *dtype=None*, *copy=False*, *verify_integrity=True*)

Pandas array for interval data that are closed on the same side.

New in version 0.24.0.

Parameters

data [array-like (1-dimensional)] Array-like containing Interval objects from which to build the IntervalArray.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

dtype [dtype or None, default None] If None, dtype will be inferred.

copy [bool, default False] Copy the input data.

verify_integrity [bool, default True] Verify that the IntervalArray is valid.

See also:

Index The base pandas Index type.
Interval A bounded slice-like interval; the elements of an IntervalArray.
interval_range Function to create a fixed frequency IntervalIndex.
cut Bin values into discrete Intervals.
qcut Bin values into equal-sized Intervals based on rank or sample quantiles.

Notes

See the user guide for more.

Examples

A new `IntervalArray` can be constructed directly from an array-like of `Interval` objects:

```
>>> pd.arrays.IntervalArray([pd.Interval(0, 1), pd.Interval(1, 5)])
<IntervalArray>
[(0, 1], (1, 5]]
Length: 2, closed: right, dtype: interval[int64]
```

It may also be constructed using one of the constructor methods: *IntervalArray.from_arrays()*, *IntervalArray.from_breaks()*, and *IntervalArray.from_tuples()*.

Attributes

left	Return the left endpoints of each Interval in the IntervalArray as an Index.
right	Return the right endpoints of each Interval in the IntervalArray as an Index.
closed	Whether the intervals are closed on the left-side, right-side, both or neither.
mid	Return the midpoint of each Interval in the IntervalArray as an Index.

continues on next page

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length	Return an Index with entries denoting the length of each Interval in the IntervalArray.
is_empty	Indicates if an interval is empty, meaning it contains no points.
is_non_overlapping_monotonic	Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

pandas.arrays.IntervalArray.left

property IntervalArray.**left**
Return the left endpoints of each Interval in the IntervalArray as an Index.

pandas.arrays.IntervalArray.right

property IntervalArray.**right**
Return the right endpoints of each Interval in the IntervalArray as an Index.

pandas.arrays.IntervalArray.closed

property IntervalArray.**closed**
Whether the intervals are closed on the left-side, right-side, both or neither.

pandas.arrays.IntervalArray.mid

property IntervalArray.**mid**
Return the midpoint of each Interval in the IntervalArray as an Index.

pandas.arrays.IntervalArray.length

property IntervalArray.**length**
Return an Index with entries denoting the length of each Interval in the IntervalArray.

pandas.arrays.IntervalArray.is_empty

IntervalArray.**is_empty**
Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

Returns

bool or ndarray A boolean indicating if a scalar `Interval` is empty, or a boolean `ndarray` positionally indicating if an `Interval` in an `IntervalArray` or `IntervalIndex` is empty.

Examples

An `Interval` that contains points is not empty:

```
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An `Interval` that does not contain any points is empty:

```
>>> pd.Interval(0, 0, closed='right').is_empty
True
>>> pd.Interval(0, 0, closed='left').is_empty
True
>>> pd.Interval(0, 0, closed='neither').is_empty
True
```

An `Interval` that contains a single point is not empty:

```
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An `IntervalArray` or `IntervalIndex` returns a boolean `ndarray` positionally indicating if an `Interval` is empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'),
...        pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

pandas.arrays.IntervalArray.is_non_overlapping_monotonic

property IntervalArray.**is_non_overlapping_monotonic**

Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

Methods

from_arrays(left, right[, closed, copy, dtype])	Construct from two arrays defining the left and right bounds.
from_tuples(data[, closed, copy, dtype])	Construct an IntervalArray from an array-like of tuples.
from_breaks(breaks[, closed, copy, dtype])	Construct an IntervalArray from an array of splits.
contains(other)	Check elementwise if the Intervals contain the value.
overlaps(other)	Check elementwise if an Interval overlaps the values in the IntervalArray.

continues on next page

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set_closed(closed)	Return an IntervalArray identical to the current one, but closed on the specified side.
to_tuples([na_tuple])	Return an ndarray of tuples of the form (left, right).

pandas.arrays.IntervalArray.from_arrays

classmethod IntervalArray.**from_arrays**(*left*, *right*, *closed='right'*, *copy=False*, *dtype=None*)

Construct from two arrays defining the left and right bounds.

Parameters

left [array-like (1-dimensional)] Left bounds for each interval.

right [array-like (1-dimensional)] Right bounds for each interval.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

copy [bool, default False] Copy the data.

dtype [dtype, optional] If None, dtype will be inferred.

Returns

IntervalArray

Raises

ValueError When a value is missing in only one of *left* or *right*. When a value in *left* is greater than the corresponding value in *right*.

See also:

interval_range Function to create a fixed frequency IntervalIndex.

IntervalArray.from_breaks Construct an IntervalArray from an array of splits.

IntervalArray.from_tuples Construct an IntervalArray from an array-like of tuples.

Notes

Each element of *left* must be less than or equal to the *right* element at the same position. If an element is missing, it must be missing in both *left* and *right*. A TypeError is raised when using an unsupported type for *left* or *right*. At the moment, 'category', 'object', and 'string' subtypes are not supported.

```
>>> pd.arrays.IntervalArray.from_arrays([0, 1, 2], [1, 2, 3])
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
```

pandas.arrays.IntervalArray.from_tuples

classmethod IntervalArray.**from_tuples**(*data*, *closed='right'*, *copy=False*, *dtype=None*)

Construct an IntervalArray from an array-like of tuples.

Parameters

data [array-like (1-dimensional)] Array of tuples.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

copy [bool, default False] By-default copy the data, this is compat only and ignored.

dtype [dtype or None, default None] If None, dtype will be inferred.

Returns

IntervalArray

See also:

interval_range Function to create a fixed frequency IntervalIndex.

IntervalArray.from_arrays Construct an IntervalArray from a left and right array.

IntervalArray.from_breaks Construct an IntervalArray from an array of splits.

Examples

```
>>> pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 2)])
<IntervalArray>
[(0, 1], (1, 2]]
Length: 2, closed: right, dtype: interval[int64]
```

pandas.arrays.IntervalArray.from_breaks

classmethod IntervalArray.**from_breaks**(*breaks*, *closed='right'*, *copy=False*, *dtype=None*)

Construct an IntervalArray from an array of splits.

Parameters

breaks [array-like (1-dimensional)] Left and right bounds for each interval.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

copy [bool, default False] Copy the data.

dtype [dtype or None, default None] If None, dtype will be inferred.

Returns

IntervalArray

See also:

interval_range Function to create a fixed frequency IntervalIndex.

IntervalArray.from_arrays Construct from a left and right array.

IntervalArray.from_tuples Construct from a sequence of tuples.

Examples

```
>>> pd.arrays.IntervalArray.from_breaks([0, 1, 2, 3])
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
```

pandas.arrays.IntervalArray.contains

IntervalArray.**contains**(*other*)

Check elementwise if the Intervals contain the value.

Return a boolean mask whether the value is contained in the Intervals of the IntervalArray.

New in version 0.25.0.

Parameters

other [scalar] The value to check whether it is contained in the Intervals.

Returns

boolean array

See also:

Interval.contains Check whether Interval object contains value.

IntervalArray.overlaps Check if an Interval overlaps the values in the IntervalArray.

Examples

```
>>> intervals = pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 3), (2, 4)])
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.contains(0.5)
array([ True, False, False])
```

pandas.arrays.IntervalArray.overlaps

IntervalArray.**overlaps**(*other*)

Check elementwise if an Interval overlaps the values in the IntervalArray.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

Parameters

other [IntervalArray] Interval to check against for an overlap.

Returns

ndarray Boolean array positionally indicating where an overlap occurs.

See also:

`Interval.overlaps` Check whether two Interval objects overlap.

Examples

```
>>> data = [(0, 1), (1, 3), (2, 4)]
>>> intervals = pd.arrays.IntervalArray.from_tuples(data)
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.overlaps(pd.Interval(0.5, 1.5))
array([ True,  True, False])
```

Intervals that share closed endpoints overlap:

```
>>> intervals.overlaps(pd.Interval(1, 3, closed='left'))
array([ True,  True, True])
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> intervals.overlaps(pd.Interval(1, 2, closed='right'))
array([False,  True, False])
```

pandas.arrays.IntervalArray.set_closed

`IntervalArray.`**`set_closed`**`(`*`closed`*`)`

Return an IntervalArray identical to the current one, but closed on the specified side.

New in version 0.24.0.

Parameters

closed [{'left', 'right', 'both', 'neither'}] Whether the intervals are closed on the left-side, right-side, both or neither.

Returns

new_index [IntervalArray]

Examples

```
>>> index = pd.arrays.IntervalArray.from_breaks(range(4))
>>> index
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
>>> index.set_closed('both')
<IntervalArray>
[[0, 1], [1, 2], [2, 3]]
Length: 3, closed: both, dtype: interval[int64]
```

pandas.arrays.IntervalArray.to_tuples

IntervalArray.**to_tuples**(*na_tuple=True*)

Return an ndarray of tuples of the form (left, right).

Parameters

na_tuple [bool, default True] Returns NA as a tuple if True, `(nan, nan)`, or just as the NA value itself if False, `nan`.

Returns

tuples: ndarray

IntervalDtype([subtype])	An ExtensionDtype for Interval data.

pandas.IntervalDtype

class pandas.**IntervalDtype**(*subtype=None*)

An ExtensionDtype for Interval data.

This is not an actual numpy dtype, but a duck type.

Parameters

subtype [str, np.dtype] The dtype of the Interval bounds.

Examples

```
>>> pd.IntervalDtype(subtype='int64')
interval[int64]
```

Attributes

subtype	The dtype of the Interval bounds.

pandas.IntervalDtype.subtype

property IntervalDtype.**subtype**
The dtype of the Interval bounds.

Methods

None	

3.5.7 Nullable integer

numpy.ndarray cannot natively represent integer-data with missing values. pandas provides this through *arrays.IntegerArray*.

arrays.IntegerArray(values, mask[, copy])	Array of integer (optional missing) values.

pandas.arrays.IntegerArray

class pandas.arrays.**IntegerArray**(*values*, *mask*, *copy=False*)
Array of integer (optional missing) values.

New in version 0.24.0.

Changed in version 1.0.0: Now uses pandas.NA as the missing value rather than numpy.nan.

> **Warning:** IntegerArray is currently experimental, and its API or internal implementation may change without warning.

We represent an IntegerArray with 2 numpy arrays:
- data: contains a numpy integer array of the appropriate dtype
- mask: a boolean array holding a mask on the data, True is missing

To construct an IntegerArray from generic array-like input, use *pandas.array()* with one of the integer dtypes (see examples).

See *Nullable integer data type* for more.

Parameters

values [numpy.ndarray] A 1-d integer-dtype array.

mask [numpy.ndarray] A 1-d boolean-dtype array indicating missing values.

copy [bool, default False] Whether to copy the *values* and *mask*.

Returns

IntegerArray

Examples

Create an IntegerArray with *pandas.array()*.

```
>>> int_array = pd.array([1, None, 3], dtype=pd.Int32Dtype())
>>> int_array
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: Int32
```

String aliases for the dtypes are also available. They are capitalized.

```
>>> pd.array([1, None, 3], dtype='Int32')
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: Int32
```

```
>>> pd.array([1, None, 3], dtype='UInt16')
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: UInt16
```

Attributes

None	

Methods

None	

Int8Dtype()	An ExtensionDtype for int8 integer data.
Int16Dtype()	An ExtensionDtype for int16 integer data.
Int32Dtype()	An ExtensionDtype for int32 integer data.
Int64Dtype()	An ExtensionDtype for int64 integer data.
UInt8Dtype()	An ExtensionDtype for uint8 integer data.
UInt16Dtype()	An ExtensionDtype for uint16 integer data.
UInt32Dtype()	An ExtensionDtype for uint32 integer data.
UInt64Dtype()	An ExtensionDtype for uint64 integer data.

pandas.Int8Dtype

class pandas.**Int8Dtype**
An ExtensionDtype for int8 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

pandas.Int16Dtype

class pandas.**Int16Dtype**
An ExtensionDtype for int16 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

pandas.Int32Dtype

class pandas.**Int32Dtype**
An ExtensionDtype for int32 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

pandas.Int64Dtype

class pandas.**Int64Dtype**

An ExtensionDtype for int64 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

pandas.UInt8Dtype

class pandas.**UInt8Dtype**

An ExtensionDtype for uint8 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

pandas.UInt16Dtype

class pandas.**UInt16Dtype**
An ExtensionDtype for uint16 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

pandas.UInt32Dtype

class pandas.**UInt32Dtype**
An ExtensionDtype for uint32 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

pandas.UInt64Dtype

class pandas.**UInt64Dtype**
An ExtensionDtype for uint64 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

Attributes

None	

Methods

None	

3.5.8 Categorical data

pandas defines a custom data type for representing data that can take only a limited, fixed set of values. The dtype of a `Categorical` can be described by a `pandas.api.types.CategoricalDtype`.

CategoricalDtype([categories, ordered])	Type for categorical data with the categories and orderedness.

pandas.CategoricalDtype

class pandas.**CategoricalDtype**(*categories=None*, *ordered=False*)

Type for categorical data with the categories and orderedness.

Parameters

categories [sequence, optional] Must be unique, and must not contain any nulls. The categories are stored in an Index, and if an index is provided the dtype of that index will be used.

ordered [bool or None, default False] Whether or not this categorical is treated as a ordered categorical. None can be used to maintain the ordered value of existing categoricals when used in operations that combine categoricals, e.g. astype, and will resolve to False if there is no existing ordered to maintain.

See also:

Categorical Represent a categorical variable in classic R / S-plus fashion.

Notes

This class is useful for specifying the type of a `Categorical` independent of the values. See *CategoricalDtype* for more.

Examples

```
>>> t = pd.CategoricalDtype(categories=['b', 'a'], ordered=True)
>>> pd.Series(['a', 'b', 'a', 'c'], dtype=t)
0      a
1      b
2      a
3    NaN
dtype: category
Categories (2, object): ['b' < 'a']
```

An empty CategoricalDtype with a specific dtype can be created by providing an empty index. As follows,

```
>>> pd.CategoricalDtype(pd.DatetimeIndex([])).categories.dtype
dtype('<M8[ns]')
```

Attributes

categories	An Index containing the unique categories allowed.
ordered	Whether the categories have an ordered relationship.

pandas.CategoricalDtype.categories

property CategoricalDtype.**categories**
An Index containing the unique categories allowed.

pandas.CategoricalDtype.ordered

property CategoricalDtype.**ordered**
Whether the categories have an ordered relationship.

Methods

None	

CategoricalDtype.categories	An Index containing the unique categories allowed.
CategoricalDtype.ordered	Whether the categories have an ordered relationship.

Categorical data can be stored in a *pandas.Categorical*

Categorical(values[, categories, ordered, ...])	Represent a categorical variable in classic R / S-plus fashion.

pandas.Categorical

class pandas.**Categorical**(*values*, *categories=None*, *ordered=None*, *dtype=None*, *fastpath=False*)
Represent a categorical variable in classic R / S-plus fashion.

Categoricals can only take on only a limited, and usually fixed, number of possible values (*categories*). In contrast to statistical categorical variables, a *Categorical* might have an order, but numerical operations (additions, divisions, ...) are not possible.

All values of the *Categorical* are either in *categories* or *np.nan*. Assigning values outside of *categories* will raise a *ValueError*. Order is defined by the order of the *categories*, not lexical order of the values.

Parameters

values [list-like] The values of the categorical. If categories are given, values not in categories will be replaced with NaN.

categories [Index-like (unique), optional] The unique categories for this categorical. If not given, the categories are assumed to be the unique values of *values* (sorted, if possible, otherwise in the order in which they appear).

ordered [bool, default False] Whether or not this categorical is treated as a ordered categorical. If True, the resulting categorical will be ordered. An ordered categorical respects, when sorted, the order of its *categories* attribute (which in turn is the *categories* argument, if provided).

dtype [CategoricalDtype] An instance of `CategoricalDtype` to use for this categorical.

Raises

ValueError If the categories do not validate.

TypeError If an explicit `ordered=True` is given but no *categories* and the *values* are not sortable.

See also:

CategoricalDtype Type for categorical data.
CategoricalIndex An Index with an underlying `Categorical`.

Notes

See the user guide for more.

Examples

```
>>> pd.Categorical([1, 2, 3, 1, 2, 3])
[1, 2, 3, 1, 2, 3]
Categories (3, int64): [1, 2, 3]
```

```
>>> pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
['a', 'b', 'c', 'a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Missing values are not included as a category.

```
>>> c = pd.Categorical([1, 2, 3, 1, 2, 3, np.nan])
>>> c
[1, 2, 3, 1, 2, 3, NaN]
Categories (3, int64): [1, 2, 3]
```

However, their presence is indicated in the *codes* attribute by code *-1*.

```
>>> c.codes
array([ 0,  1,  2,  0,  1,  2, -1], dtype=int8)
```

Ordered *Categoricals* can be sorted according to the custom order of the categories and can have a min and max value.

```
>>> c = pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'], ordered=True,
...                    categories=['c', 'b', 'a'])
>>> c
['a', 'b', 'c', 'a', 'b', 'c']
Categories (3, object): ['c' < 'b' < 'a']
```

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```
>>> c.min()
'c'
```

Attributes

categories	The categories of this categorical.
codes	The category codes of this categorical.
ordered	Whether the categories have an ordered relationship.
dtype	The CategoricalDtype for this instance.

pandas.Categorical.categories

property Categorical.**categories**

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to *categories* is a inplace operation!

Raises

ValueError If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

See also:

rename_categories Rename categories.

reorder_categories Reorder categories.

add_categories Add new categories.

remove_categories Remove the specified categories.

remove_unused_categories Remove categories which are not used.

set_categories Set the categories to the specified ones.

pandas.Categorical.codes

property Categorical.**codes**

The category codes of this categorical.

Codes are an array of integers which are the positions of the actual values in the categories array.

There is no setter, use the other categorical methods and the normal item setter to change values in the categorical.

Returns

ndarray[int] A non-writable view of the *codes* array.

pandas.Categorical.ordered

property Categorical.**ordered**
Whether the categories have an ordered relationship.

pandas.Categorical.dtype

property Categorical.**dtype**
The CategoricalDtype for this instance.

Methods

from_codes(codes[, categories, ordered, dtype])	Make a Categorical type from codes and categories or dtype.
__array__([dtype])	The numpy array interface.

pandas.Categorical.from_codes

classmethod Categorical.**from_codes**(*codes*, *categories=None*, *ordered=None*, *dtype=None*)
Make a Categorical type from codes and categories or dtype.

This constructor is useful if you already have codes and categories/dtype and so do not need the (computation intensive) factorization step, which is usually done on the constructor.

If your data does not follow this convention, please use the normal constructor.

Parameters

codes [array-like of int] An integer array, where each integer points to a category in categories or dtype.categories, or else is -1 for NaN.

categories [index-like, optional] The categories for the categorical. Items need to be unique. If the categories are not given here, then they must be provided in *dtype*.

ordered [bool, optional] Whether or not this categorical is treated as an ordered categorical. If not given here or in *dtype*, the resulting categorical will be unordered.

dtype [CategoricalDtype or "category", optional] If *CategoricalDtype*, cannot be used together with *categories* or *ordered*.

New in version 0.24.0: When *dtype* is provided, neither *categories* nor *ordered* should be provided.

Returns

Categorical

Examples

```
>>> dtype = pd.CategoricalDtype(['a', 'b'], ordered=True)
>>> pd.Categorical.from_codes(codes=[0, 1, 0, 1], dtype=dtype)
['a', 'b', 'a', 'b']
Categories (2, object): ['a' < 'b']
```

pandas.Categorical.__array__

Categorical.__array__(*dtype=None*)

The numpy array interface.

Returns

numpy.array A numpy array of either the specified dtype or, if dtype==None (default), the same dtype as categorical.categories.dtype.

The alternative *Categorical.from_codes()* constructor can be used when you have the categories and integer codes already:

Categorical.from_codes(codes[, categories, ...])	Make a Categorical type from codes and categories or dtype.

The dtype information is available on the Categorical

Categorical.dtype	The CategoricalDtype for this instance.
Categorical.categories	The categories of this categorical.
Categorical.ordered	Whether the categories have an ordered relationship.
Categorical.codes	The category codes of this categorical.

np.asarray(categorical) works by implementing the array interface. Be aware, that this converts the Categorical back to a NumPy array, so categories and order information is not preserved!

Categorical.__array__([dtype])	The numpy array interface.

A Categorical can be stored in a Series or DataFrame. To create a Series of dtype category, use cat = s.astype(dtype) or Series(..., dtype=dtype) where dtype is either

- the string 'category'
- an instance of CategoricalDtype.

If the Series is of dtype CategoricalDtype, Series.cat can be used to change the categorical data. See *Categorical accessor* for more.

3.5.9 Sparse data

Data where a single value is repeated many times (e.g. `0` or `NaN`) may be stored efficiently as a *arrays.SparseArray*.

arrays.SparseArray(data[, sparse_index, ...])	An ExtensionArray for storing sparse data.

pandas.arrays.SparseArray

class pandas.arrays.**SparseArray**(*data*, *sparse_index=None*, *index=None*, *fill_value=None*, *kind='integer'*, *dtype=None*, *copy=False*)

An ExtensionArray for storing sparse data.

Changed in version 0.24.0: Implements the ExtensionArray interface.

Parameters

data [array-like] A dense array of values to store in the SparseArray. This may contain *fill_value*.

sparse_index [SparseIndex, optional]

index [Index]

fill_value [scalar, optional] Elements in *data* that are *fill_value* are not stored in the SparseArray. For memory savings, this should be the most common value in *data*. By default, *fill_value* depends on the dtype of *data*:

data.dtype	na_value
float	`np.nan`
int	`0`
bool	False
datetime64	`pd.NaT`
timedelta64	`pd.NaT`

The fill value is potentially specified in three ways. In order of precedence, these are

1. The *fill_value* argument
2. `dtype.fill_value` if *fill_value* is None and *dtype* is a `SparseDtype`
3. `data.dtype.fill_value` if *fill_value* is None and *dtype* is not a `SparseDtype` and *data* is a `SparseArray`.

kind [{'integer', 'block'}, default 'integer'] The type of storage for sparse locations.

- 'block': Stores a *block* and *block_length* for each contiguous *span* of sparse values. This is best when sparse data tends to be clumped together, with large regions of `fill-value` values between sparse values.
- 'integer': uses an integer to store the location of each sparse value.

dtype [np.dtype or SparseDtype, optional] The dtype to use for the SparseArray. For numpy dtypes, this determines the dtype of `self.sp_values`. For SparseDtype, this determines `self.sp_values` and `self.fill_value`.

copy [bool, default False] Whether to explicitly copy the incoming *data* array.

Examples

```
>>> from pandas.arrays import SparseArray
>>> arr = SparseArray([0, 0, 1, 2])
>>> arr
[0, 0, 1, 2]
Fill: 0
IntIndex
Indices: array([2, 3], dtype=int32)
```

Attributes

None	

Methods

None	

SparseDtype([dtype, fill_value])	Dtype for data stored in `SparseArray`.

pandas.SparseDtype

class pandas.**SparseDtype**(*dtype=<class 'numpy.float64'>*, *fill_value=None*)

Dtype for data stored in `SparseArray`.

This dtype implements the pandas ExtensionDtype interface.

New in version 0.24.0.

Parameters

dtype [str, ExtensionDtype, numpy.dtype, type, default numpy.float64] The dtype of the underlying array storing the non-fill value values.

fill_value [scalar, optional] The scalar value not stored in the SparseArray. By default, this depends on *dtype*.

dtype	na_value
float	`np.nan`
int	`0`
bool	`False`
datetime64	`pd.NaT`
timedelta64	`pd.NaT`

The default value may be overridden by specifying a *fill_value*.

Attributes

None	

Methods

None	

The `Series.sparse` accessor may be used to access sparse-specific attributes and methods if the *Series* contains sparse values. See *Sparse accessor* for more.

3.5.10 Text data

When working with text data, where each valid element is a string or missing, we recommend using *StringDtype* (with the alias `"string"`).

arrays.StringArray(values[, copy])	Extension array for string data.

pandas.arrays.StringArray

class pandas.arrays.**StringArray**(*values*, *copy=False*)

Extension array for string data.

New in version 1.0.0.

> **Warning:** StringArray is considered experimental. The implementation and parts of the API may change without warning.

Parameters

values [array-like] The array of data.

> **Warning:** Currently, this expects an object-dtype ndarray where the elements are Python strings or `pandas.NA`. This may change without warning in the future. Use *pandas.array()* with `dtype="string"` for a stable way of creating a *StringArray* from any sequence.

copy [bool, default False] Whether to copy the array of data.

See also:

array The recommended function for creating a StringArray.
Series.str The string methods are available on Series backed by a StringArray.

Notes

StringArray returns a BooleanArray for comparison methods.

Examples

```
>>> pd.array(['This is', 'some text', None, 'data.'], dtype="string")
<StringArray>
['This is', 'some text', <NA>, 'data.']
Length: 4, dtype: string
```

Unlike arrays instantiated with `dtype="object"`, `StringArray` will convert the values to strings.

```
>>> pd.array(['1', 1], dtype="object")
<PandasArray>
['1', 1]
Length: 2, dtype: object
>>> pd.array(['1', 1], dtype="string")
<StringArray>
['1', '1']
Length: 2, dtype: string
```

However, instantiating StringArrays directly with non-strings will raise an error.

For comparison methods, *StringArray* returns a `pandas.BooleanArray`:

```
>>> pd.array(["a", None, "c"], dtype="string") == "a"
<BooleanArray>
[True, <NA>, False]
Length: 3, dtype: boolean
```

Attributes

None	

Methods

None	

StringDtype()	Extension dtype for string data.

pandas.StringDtype

class pandas.**StringDtype**
Extension dtype for string data.

New in version 1.0.0.

> **Warning:** StringDtype is considered experimental. The implementation and parts of the API may change without warning.
>
> In particular, StringDtype.na_value may change to no longer be `numpy.nan`.

Examples

```
>>> pd.StringDtype()
StringDtype
```

Attributes

None	

Methods

None	

The `Series.str` accessor is available for `Series` backed by a *arrays.StringArray*. See *String handling* for more.

3.5.11 Boolean data with missing values

The boolean dtype (with the alias `"boolean"`) provides support for storing boolean data (True, False values) with missing values, which is not possible with a bool `numpy.ndarray`.

arrays.BooleanArray(values, mask[, copy])	Array of boolean (True/False) data with missing values.

pandas.arrays.BooleanArray

class pandas.arrays.**BooleanArray**(*values*, *mask*, *copy=False*)
Array of boolean (True/False) data with missing values.

This is a pandas Extension array for boolean data, under the hood represented by 2 numpy arrays: a boolean array with the data and a boolean array with the mask (True indicating missing).

BooleanArray implements Kleene logic (sometimes called three-value logic) for logical operations. See *Kleene logical operations* for more.

To construct an BooleanArray from generic array-like input, use *pandas.array()* specifying `dtype="boolean"` (see examples below).

New in version 1.0.0.

Warning: BooleanArray is considered experimental. The implementation and parts of the API may change without warning.

Parameters

values [numpy.ndarray] A 1-d boolean-dtype array with the data.

mask [numpy.ndarray] A 1-d boolean-dtype array indicating missing values (True indicates missing).

copy [bool, default False] Whether to copy the *values* and *mask* arrays.

Returns

BooleanArray

Examples

Create an BooleanArray with *pandas.array()*:

```
>>> pd.array([True, False, None], dtype="boolean")
<BooleanArray>
[True, False, <NA>]
Length: 3, dtype: boolean
```

Attributes

None	

Methods

None	

BooleanDtype()	Extension dtype for boolean data.

pandas.BooleanDtype

class pandas.**BooleanDtype**

Extension dtype for boolean data.

New in version 1.0.0.

Warning: BooleanDtype is considered experimental. The implementation and parts of the API may change without warning.

Examples

```
>>> pd.BooleanDtype()
BooleanDtype
```

Attributes

None	

Methods

None	

3.6 Index objects

3.6.1 Index

Many of these methods or variants thereof are available on the objects that contain an index (Series/DataFrame) and those should most likely be used before calling these methods directly.

Index([data, dtype, copy, name, tupleize_cols])	Immutable sequence used for indexing and alignment.

pandas.Index

class pandas.**Index**(*data=None*, *dtype=None*, *copy=False*, *name=None*, *tupleize_cols=True*, ***kwargs*)

Immutable sequence used for indexing and alignment. The basic object storing axis labels for all pandas objects.

Parameters

data [array-like (1-dimensional)]

dtype [NumPy dtype (default: object)] If dtype is None, we find the dtype that best fits the data. If an actual dtype is provided, we coerce to that dtype if it's safe. Otherwise, an error will be raised.

copy [bool] Make a copy of input ndarray.

name [object] Name to be stored in the index.

tupleize_cols [bool (default: True)] When True, attempt to create a MultiIndex if possible.

See also:

RangeIndex Index implementing a monotonic integer range.
CategoricalIndex Index of *Categorical* s.
MultiIndex A multi-level, or hierarchical Index.
IntervalIndex An Index of *Interval* s.
DatetimeIndex Index of datetime64 data.
TimedeltaIndex Index of timedelta64 data.
PeriodIndex Index of Period data.
Int64Index A special case of *Index* with purely integer labels.

UInt64Index A special case of *Index* with purely unsigned integer labels.
Float64Index A special case of *Index* with purely float labels.

Notes

An Index instance can **only** contain hashable objects

Examples

```
>>> pd.Index([1, 2, 3])
Int64Index([1, 2, 3], dtype='int64')
```

```
>>> pd.Index(list('abc'))
Index(['a', 'b', 'c'], dtype='object')
```

Attributes

T	Return the transpose, which is by definition self.
array	The ExtensionArray of the data backing this Series or Index.
asi8	Integer representation of the values.
dtype	Return the dtype object of the underlying data.
has_duplicates	Check if the Index has duplicate values.
hasnans	Return if I have any nans; enables various perf speedups.
inferred_type	Return a string of the type inferred from the values.
is_all_dates	Whether or not the index values only consist of dates.
is_monotonic	Alias for is_monotonic_increasing.
is_monotonic_decreasing	Return if the index is monotonic decreasing (only equal or decreasing) values.
is_monotonic_increasing	Return if the index is monotonic increasing (only equal or increasing) values.
is_unique	Return if the index has unique values.
name	Return Index or MultiIndex name.
nbytes	Return the number of bytes in the underlying data.
ndim	Number of dimensions of the underlying data, by definition 1.
nlevels	Number of levels.
shape	Return a tuple of the shape of the underlying data.
size	Return the number of elements in the underlying data.
values	Return an array representing the data in the Index.

pandas.Index.T

property Index.**T**
Return the transpose, which is by definition self.

pandas.Index.array

Index.**array**
The ExtensionArray of the data backing this Series or Index.

New in version 0.24.0.

Returns

ExtensionArray An ExtensionArray of the values stored within. For extension types, this is the actual array. For NumPy native types, this is a thin (no copy) wrapper around `numpy.ndarray`.

`.array` differs `.values` which may require converting the data to a different form.

See also:

Index.to_numpy Similar method that always returns a NumPy array.

Series.to_numpy Similar method that always returns a NumPy array.

Notes

This table lays out the different array types for each extension dtype within pandas.

dtype	array type
category	Categorical
period	PeriodArray
interval	IntervalArray
IntegerNA	IntegerArray
string	StringArray
boolean	BooleanArray
datetime64[ns, tz]	DatetimeArray

For any 3rd-party extension types, the array type will be an ExtensionArray.

For all remaining dtypes `.array` will be a `arrays.NumpyExtensionArray` wrapping the actual ndarray stored within. If you absolutely need a NumPy array (possibly with copying / coercing data), then use *`Series.to_numpy()`* instead.

Examples

For regular NumPy types like int, and float, a PandasArray is returned.

```
>>> pd.Series([1, 2, 3]).array
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
```

For extension types, like Categorical, the actual ExtensionArray is returned

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.array
['a', 'b', 'a']
Categories (2, object): ['a', 'b']
```

pandas.Index.asi8

property Index.**asi8**

Integer representation of the values.

Returns

ndarray An ndarray with int64 dtype.

pandas.Index.dtype

Index.**dtype**

Return the dtype object of the underlying data.

pandas.Index.has_duplicates

property Index.**has_duplicates**

Check if the Index has duplicate values.

Returns

bool Whether or not the Index has duplicate values.

Examples

```
>>> idx = pd.Index([1, 5, 7, 7])
>>> idx.has_duplicates
True
```

```
>>> idx = pd.Index([1, 5, 7])
>>> idx.has_duplicates
False
```

```
>>> idx = pd.Index(["Watermelon", "Orange", "Apple",
...                 "Watermelon"]).astype("category")
>>> idx.has_duplicates
True
```

```
>>> idx = pd.Index(["Orange", "Apple",
...                 "Watermelon"]).astype("category")
>>> idx.has_duplicates
False
```

pandas.Index.hasnans

Index.**hasnans**
Return if I have any nans; enables various perf speedups.

pandas.Index.inferred_type

Index.**inferred_type**
Return a string of the type inferred from the values.

pandas.Index.is_all_dates

Index.**is_all_dates**
Whether or not the index values only consist of dates.

pandas.Index.is_monotonic

property Index.**is_monotonic**
Alias for is_monotonic_increasing.

pandas.Index.is_monotonic_decreasing

property Index.**is_monotonic_decreasing**
Return if the index is monotonic decreasing (only equal or decreasing) values.

Examples

```
>>> Index([3, 2, 1]).is_monotonic_decreasing
True
>>> Index([3, 2, 2]).is_monotonic_decreasing
True
>>> Index([3, 1, 2]).is_monotonic_decreasing
False
```

pandas.Index.is_monotonic_increasing

property Index.**is_monotonic_increasing**
Return if the index is monotonic increasing (only equal or increasing) values.

Examples

```
>>> Index([1, 2, 3]).is_monotonic_increasing
True
>>> Index([1, 2, 2]).is_monotonic_increasing
True
>>> Index([1, 3, 2]).is_monotonic_increasing
False
```

pandas.Index.is_unique

Index.**is_unique**
Return if the index has unique values.

pandas.Index.name

property Index.**name**
Return Index or MultiIndex name.

pandas.Index.nbytes

property Index.**nbytes**
Return the number of bytes in the underlying data.

pandas.Index.ndim

property Index.**ndim**
Number of dimensions of the underlying data, by definition 1.

pandas.Index.nlevels

property Index.**nlevels**
Number of levels.

pandas.Index.shape

property Index.**shape**
Return a tuple of the shape of the underlying data.

pandas.Index.size

property Index.**size**
Return the number of elements in the underlying data.

pandas.Index.values

property Index.**values**
Return an array representing the data in the Index.

> **Warning:** We recommend using *Index.array* or *Index.to_numpy()*, depending on whether you need a reference to the underlying data or a NumPy array.

Returns

array: numpy.ndarray or ExtensionArray

See also:

Index.array Reference to the underlying data.

Index.to_numpy A NumPy array representing the underlying data.

empty	
names	

Methods

all()	Return whether all elements are Truthy.
any(*args, **kwargs)	Return whether any element is Truthy.
append(other)	Append a collection of Index options together.
argmax([axis, skipna])	Return int position of the largest value in the Series.
argmin([axis, skipna])	Return int position of the smallest value in the Series.
argsort(*args, **kwargs)	Return the integer indices that would sort the index.
asof(label)	Return the label from the index, or, if not present, the previous one.
asof_locs(where, mask)	Return the locations (indices) of labels in the index.
astype(dtype[, copy])	Create an Index with values cast to dtypes.
copy([name, deep, dtype, names])	Make a copy of this object.
delete(loc)	Make new Index with passed location(-s) deleted.
difference(other[, sort])	Return a new Index with elements of index not in *other*.

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drop(labels[, errors])	Make new Index with passed list of labels deleted.
drop_duplicates([keep])	Return Index with duplicate values removed.
droplevel([level])	Return index with requested level(s) removed.
dropna([how])	Return Index without NA/NaN values.
duplicated([keep])	Indicate duplicate index values.
equals(other)	Determine if two Index object are equal.
factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable.
fillna([value, downcast])	Fill NA/NaN values with the specified value.
format([name, formatter, na_rep])	Render a string representation of the Index.
get_indexer(target[, method, limit, tolerance])	Compute indexer and mask for new index given the current index.
get_indexer_for(target, **kwargs)	Guaranteed return of an indexer even when non-unique.
get_indexer_non_unique(target)	Compute indexer and mask for new index given the current index.
get_level_values(level)	Return an Index of values for requested level.
get_loc(key[, method, tolerance])	Get integer location, slice or boolean mask for requested label.
get_slice_bound(label, side, kind)	Calculate slice bound that corresponds to given label.
get_value(series, key)	Fast lookup of value from 1-dimensional ndarray.
groupby(values)	Group the index labels by a given array of values.
holds_integer()	Whether the type is an integer type.
identical(other)	Similar to equals, but checks that object attributes and types are also equal.
insert(loc, item)	Make new Index inserting new item at location.
intersection(other[, sort])	Form the intersection of two Index objects.
is_(other)	More flexible, faster check like `is` but that works through views.
is_boolean()	Check if the Index only consists of booleans.
is_categorical()	Check if the Index holds categorical data.
is_floating()	Check if the Index is a floating type.
is_integer()	Check if the Index only consists of integers.
is_interval()	Check if the Index holds Interval objects.
is_mixed()	Check if the Index holds data with mixed data types.
is_numeric()	Check if the Index only consists of numeric data.
is_object()	Check if the Index is of the object dtype.
is_type_compatible(kind)	Whether the index type is compatible with the provided type.
isin(values[, level])	Return a boolean array where the index values are in *values*.
isna()	Detect missing values.
isnull()	Detect missing values.
item()	Return the first element of the underlying data as a Python scalar.
join(other[, how, level, return_indexers, sort])	Compute join_index and indexers to conform data structures to the new index.
map(mapper[, na_action])	Map values using input correspondence (a dict, Series, or function).
max([axis, skipna])	Return the maximum value of the Index.
memory_usage([deep])	Memory usage of the values.

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Table 132 – continued from previous page

min([axis, skipna])	Return the minimum value of the Index.
notna()	Detect existing (non-missing) values.
notnull()	Detect existing (non-missing) values.
nunique([dropna])	Return number of unique elements in the object.
putmask(mask, value)	Return a new Index of the values set with the mask.
ravel([order])	Return an ndarray of the flattened values of the underlying data.
reindex(target[, method, level, limit, ...])	Create index with target's values.
rename(name[, inplace])	Alter Index or MultiIndex name.
repeat(repeats[, axis])	Repeat elements of a Index.
searchsorted(value[, side, sorter])	Find indices where elements should be inserted to maintain order.
set_names(names[, level, inplace])	Set Index or MultiIndex name.
set_value(arr, key, value)	(DEPRECATED) Fast lookup of value from 1-dimensional ndarray.
shift([periods, freq])	Shift index by desired number of time frequency increments.
slice_indexer([start, end, step, kind])	Compute the slice indexer for input labels and step.
slice_locs([start, end, step, kind])	Compute slice locations for input labels.
sort(*args, **kwargs)	Use sort_values instead.
sort_values([return_indexer, ascending, ...])	Return a sorted copy of the index.
sortlevel([level, ascending, sort_remaining])	For internal compatibility with the Index API.
str	alias of `pandas.core.strings.accessor.StringMethods`
symmetric_difference(other[, result_name, sort])	Compute the symmetric difference of two Index objects.
take(indices[, axis, allow_fill, fill_value])	Return a new Index of the values selected by the indices.
to_flat_index()	Identity method.
to_frame([index, name])	Create a DataFrame with a column containing the Index.
to_list()	Return a list of the values.
to_native_types([slicer])	(DEPRECATED) Format specified values of *self* and return them.
to_numpy([dtype, copy, na_value])	A NumPy ndarray representing the values in this Series or Index.
to_series([index, name])	Create a Series with both index and values equal to the index keys.
tolist()	Return a list of the values.
transpose(*args, **kwargs)	Return the transpose, which is by definition self.
union(other[, sort])	Form the union of two Index objects.
unique([level])	Return unique values in the index.
value_counts([normalize, sort, ascending, ...])	Return a Series containing counts of unique values.
where(cond[, other])	Replace values where the condition is False.

pandas.Index.all

Index.**all**()

Return whether all elements are Truthy.

Parameters

***args** These parameters will be passed to numpy.all.

****kwargs** These parameters will be passed to numpy.all.

Returns

all [bool or array_like (if axis is specified)] A single element array_like may be converted to bool.

See also:

Index.any Return whether any element in an Index is True.

Series.any Return whether any element in a Series is True.

Series.all Return whether all elements in a Series are True.

Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

Examples

all

True, because nonzero integers are considered True.

```
>>> pd.Index([1, 2, 3]).all()
True
```

False, because `0` is considered False.

```
>>> pd.Index([0, 1, 2]).all()
False
```

any

True, because `1` is considered True.

```
>>> pd.Index([0, 0, 1]).any()
True
```

False, because `0` is considered False.

```
>>> pd.Index([0, 0, 0]).any()
False
```

pandas.Index.any

Index.**any**(**args*, ***kwargs*)

Return whether any element is Truthy.

Parameters

***args** These parameters will be passed to numpy.any.

****kwargs** These parameters will be passed to numpy.any.

Returns

any [bool or array_like (if axis is specified)] A single element array_like may be converted to bool.

See also:

Index.all Return whether all elements are True.

Series.all Return whether all elements are True.

Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

Examples

```
>>> index = pd.Index([0, 1, 2])
>>> index.any()
True
```

```
>>> index = pd.Index([0, 0, 0])
>>> index.any()
False
```

pandas.Index.append

Index.**append**(*other*)

Append a collection of Index options together.

Parameters

other [Index or list/tuple of indices]

Returns

appended [Index]

pandas.Index.argmax

Index.**argmax**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return int position of the largest value in the Series.

If the maximum is achieved in multiple locations, the first row position is returned.

Parameters

axis [{None}] Dummy argument for consistency with Series.

skipna [bool, default True] Exclude NA/null values when showing the result.

***args, **kwargs** Additional arguments and keywords for compatibility with NumPy.

Returns

int Row position of the maximum value.

See also:

Series.argmax Return position of the maximum value.

Series.argmin Return position of the minimum value.

numpy.ndarray.argmax Equivalent method for numpy arrays.

Series.idxmax Return index label of the maximum values.

Series.idxmin Return index label of the minimum values.

Examples

Consider dataset containing cereal calories

```
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,
...                'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
>>> s
Corn Flakes              100.0
Almond Delight           110.0
Cinnamon Toast Crunch    120.0
Cocoa Puff               110.0
dtype: float64
```

```
>>> s.argmax()
2
>>> s.argmin()
0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.

pandas.Index.argmin

Index.**argmin**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return int position of the smallest value in the Series.

If the minimum is achieved in multiple locations, the first row position is returned.

Parameters

axis [{None}] Dummy argument for consistency with Series.

skipna [bool, default True] Exclude NA/null values when showing the result.

***args, **kwargs** Additional arguments and keywords for compatibility with NumPy.

Returns

int Row position of the minimum value.

See also:

Series.argmin Return position of the minimum value.

Series.argmax Return position of the maximum value.

numpy.ndarray.argmin Equivalent method for numpy arrays.

Series.idxmax Return index label of the maximum values.

Series.idxmin Return index label of the minimum values.

Examples

Consider dataset containing cereal calories

```
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,
...                'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
>>> s
Corn Flakes              100.0
Almond Delight           110.0
Cinnamon Toast Crunch    120.0
Cocoa Puff               110.0
dtype: float64
```

```
>>> s.argmax()
2
>>> s.argmin()
0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.

pandas.Index.argsort

Index.**argsort**(**args*, ***kwargs*)

Return the integer indices that would sort the index.

Parameters

***args** Passed to *numpy.ndarray.argsort*.

****kwargs** Passed to *numpy.ndarray.argsort*.

Returns

numpy.ndarray Integer indices that would sort the index if used as an indexer.

See also:

numpy.argsort Similar method for NumPy arrays.

Index.sort_values Return sorted copy of Index.

Examples

```
>>> idx = pd.Index(['b', 'a', 'd', 'c'])
>>> idx
Index(['b', 'a', 'd', 'c'], dtype='object')
```

```
>>> order = idx.argsort()
>>> order
array([1, 0, 3, 2])
```

```
>>> idx[order]
Index(['a', 'b', 'c', 'd'], dtype='object')
```

pandas.Index.asof

Index.**asof**(*label*)

Return the label from the index, or, if not present, the previous one.

Assuming that the index is sorted, return the passed index label if it is in the index, or return the previous index label if the passed one is not in the index.

Parameters

label [object] The label up to which the method returns the latest index label.

Returns

object The passed label if it is in the index. The previous label if the passed label is not in the sorted index or *NaN* if there is no such label.

See also:

Series.asof Return the latest value in a Series up to the passed index.

merge_asof Perform an asof merge (similar to left join but it matches on nearest key rather than equal key).

Index.get_loc An *asof* is a thin wrapper around *get_loc* with method='pad'.

Examples

Index.asof returns the latest index label up to the passed label.

```
>>> idx = pd.Index(['2013-12-31', '2014-01-02', '2014-01-03'])
>>> idx.asof('2014-01-01')
'2013-12-31'
```

If the label is in the index, the method returns the passed label.

```
>>> idx.asof('2014-01-02')
'2014-01-02'
```

If all of the labels in the index are later than the passed label, NaN is returned.

```
>>> idx.asof('1999-01-02')
nan
```

If the index is not sorted, an error is raised.

```
>>> idx_not_sorted = pd.Index(['2013-12-31', '2015-01-02',
...                            '2014-01-03'])
>>> idx_not_sorted.asof('2013-12-31')
Traceback (most recent call last):
ValueError: index must be monotonic increasing or decreasing
```

pandas.Index.asof_locs

Index.**asof_locs**(*where*, *mask*)

Return the locations (indices) of labels in the index.

As in the *asof* function, if the label (a particular entry in *where*) is not in the index, the latest index label up to the passed label is chosen and its index returned.

If all of the labels in the index are later than a label in *where*, -1 is returned.

mask is used to ignore NA values in the index during calculation.

Parameters

where [Index] An Index consisting of an array of timestamps.

mask [array-like] Array of booleans denoting where values in the original data are not NA.

Returns

numpy.ndarray An array of locations (indices) of the labels from the Index which correspond to the return values of the *asof* function for every element in *where*.

pandas.Index.astype

Index.**astype**(*dtype*, *copy=True*)

Create an Index with values cast to dtypes.

The class of a new Index is determined by dtype. When conversion is impossible, a TypeError exception is raised.

Parameters

dtype [numpy dtype or pandas type] Note that any signed integer *dtype* is treated as `'int64'`, and any unsigned integer *dtype* is treated as `'uint64'`, regardless of the size.

copy [bool, default True] By default, astype always returns a newly allocated object. If copy is set to False and internal requirements on dtype are satisfied, the original data is used to create a new Index or the original Index is returned.

Returns

Index Index with values cast to specified dtype.

pandas.Index.copy

Index.**copy**(*name=None*, *deep=False*, *dtype=None*, *names=None*)

Make a copy of this object.

Name and dtype sets those attributes on the new object.

Parameters

name [Label, optional] Set name for new object.

deep [bool, default False]

dtype [numpy dtype or pandas type, optional] Set dtype for new object.

Deprecated since version 1.2.0: use `astype` method instead.

names [list-like, optional] Kept for compatibility with MultiIndex. Should not be used.

Returns

Index Index refer to new object which is a copy of this object.

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.Index.delete

Index.**delete**(*loc*)

Make new Index with passed location(-s) deleted.

Parameters

loc [int or list of int] Location of item(-s) which will be deleted. Use a list of locations to delete more than one value at the same time.

Returns

Index New Index with passed location(-s) deleted.

See also:

numpy.delete Delete any rows and column from NumPy array (ndarray).

Examples

```
>>> idx = pd.Index(['a', 'b', 'c'])
>>> idx.delete(1)
Index(['a', 'c'], dtype='object')
```

```
>>> idx = pd.Index(['a', 'b', 'c'])
>>> idx.delete([0, 2])
Index(['b'], dtype='object')
```

pandas.Index.difference

Index.**difference**(*other*, *sort=None*)

Return a new Index with elements of index not in *other*.

This is the set difference of two Index objects.

Parameters

other [Index or array-like]

sort [False or None, default None] Whether to sort the resulting index. By default, the values are attempted to be sorted, but any TypeError from incomparable elements is caught by pandas.

- None : Attempt to sort the result, but catch any TypeErrors from comparing incomparable elements.
- False : Do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from `True` to `None` (without change in behaviour).

Returns

difference [Index]

Examples

```
>>> idx1 = pd.Index([2, 1, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.difference(idx2)
Int64Index([1, 2], dtype='int64')
>>> idx1.difference(idx2, sort=False)
Int64Index([2, 1], dtype='int64')
```

pandas.Index.drop

Index.**drop**(*labels*, *errors='raise'*)

Make new Index with passed list of labels deleted.

Parameters

labels [array-like]

errors [{'ignore', 'raise'}, default 'raise'] If 'ignore', suppress error and existing labels are dropped.

Returns

dropped [Index]

Raises

KeyError If not all of the labels are found in the selected axis

pandas.Index.drop_duplicates

Index.**drop_duplicates**(*keep='first'*)

Return Index with duplicate values removed.

Parameters

keep [{'first', 'last', False}, default 'first']

- 'first' : Drop duplicates except for the first occurrence.
- 'last' : Drop duplicates except for the last occurrence.
- False : Drop all duplicates.

Returns

deduplicated [Index]

See also:

Series.drop_duplicates Equivalent method on Series.

DataFrame.drop_duplicates Equivalent method on DataFrame.

Index.duplicated Related method on Index, indicating duplicate Index values.

Examples

Generate an pandas.Index with duplicate values.

```
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'])
```

The *keep* parameter controls which duplicate values are removed. The value 'first' keeps the first occurrence for each set of duplicated entries. The default value of keep is 'first'.

```
>>> idx.drop_duplicates(keep='first')
Index(['lama', 'cow', 'beetle', 'hippo'], dtype='object')
```

The value 'last' keeps the last occurrence for each set of duplicated entries.

```
>>> idx.drop_duplicates(keep='last')
Index(['cow', 'beetle', 'lama', 'hippo'], dtype='object')
```

The value `False` discards all sets of duplicated entries.

```
>>> idx.drop_duplicates(keep=False)
Index(['cow', 'beetle', 'hippo'], dtype='object')
```

pandas.Index.droplevel

`Index.`**`droplevel`**(*level=0*)

Return index with requested level(s) removed.

If resulting index has only 1 level left, the result will be of Index type, not MultiIndex.

Parameters

level [int, str, or list-like, default 0] If a string is given, must be the name of a level If list-like, elements must be names or indexes of levels.

Returns

Index or MultiIndex

Examples

```
>>> mi = pd.MultiIndex.from_arrays(
... [[1, 2], [3, 4], [5, 6]], names=['x', 'y', 'z'])
>>> mi
MultiIndex([(1, 3, 5),
            (2, 4, 6)],
           names=['x', 'y', 'z'])
```

```
>>> mi.droplevel()
MultiIndex([(3, 5),
            (4, 6)],
           names=['y', 'z'])
```

```
>>> mi.droplevel(2)
MultiIndex([(1, 3),
            (2, 4)],
           names=['x', 'y'])
```

```
>>> mi.droplevel('z')
MultiIndex([(1, 3),
            (2, 4)],
           names=['x', 'y'])
```

```
>>> mi.droplevel(['x', 'y'])
Int64Index([5, 6], dtype='int64', name='z')
```

pandas.Index.dropna

Index.**dropna**(*how='any'*)

Return Index without NA/NaN values.

Parameters

how [{'any', 'all'}, default 'any'] If the Index is a MultiIndex, drop the value when any or all levels are NaN.

Returns

Index

pandas.Index.duplicated

Index.**duplicated**(*keep='first'*)

Indicate duplicate index values.

Duplicated values are indicated as `True` values in the resulting array. Either all duplicates, all except the first, or all except the last occurrence of duplicates can be indicated.

Parameters

keep [{'first', 'last', False}, default 'first'] The value or values in a set of duplicates to mark as missing.

- 'first' : Mark duplicates as `True` except for the first occurrence.
- 'last' : Mark duplicates as `True` except for the last occurrence.
- `False` : Mark all duplicates as `True`.

Returns

numpy.ndarray

See also:

Series.duplicated Equivalent method on pandas.Series.

DataFrame.duplicated Equivalent method on pandas.DataFrame.

Index.drop_duplicates Remove duplicate values from Index.

Examples

By default, for each set of duplicated values, the first occurrence is set to False and all others to True:

```
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> idx.duplicated()
array([False, False,  True, False,  True])
```

which is equivalent to

```
>>> idx.duplicated(keep='first')
array([False, False,  True, False,  True])
```

By using 'last', the last occurrence of each set of duplicated values is set on False and all others on True:

```
>>> idx.duplicated(keep='last')
array([ True, False,  True, False, False])
```

By setting keep on `False`, all duplicates are True:

```
>>> idx.duplicated(keep=False)
array([ True, False,  True, False,  True])
```

pandas.Index.equals

`Index.`**`equals`**(*other*)

Determine if two Index object are equal.

The things that are being compared are:

- The elements inside the Index object.
- The order of the elements inside the Index object.

Parameters

other [Any] The other object to compare against.

Returns

bool True if "other" is an Index and it has the same elements and order as the calling index; False otherwise.

Examples

```
>>> idx1 = pd.Index([1, 2, 3])
>>> idx1
Int64Index([1, 2, 3], dtype='int64')
>>> idx1.equals(pd.Index([1, 2, 3]))
True
```

The elements inside are compared

```
>>> idx2 = pd.Index(["1", "2", "3"])
>>> idx2
Index(['1', '2', '3'], dtype='object')
```

```
>>> idx1.equals(idx2)
False
```

The order is compared

```
>>> ascending_idx = pd.Index([1, 2, 3])
>>> ascending_idx
Int64Index([1, 2, 3], dtype='int64')
>>> descending_idx = pd.Index([3, 2, 1])
>>> descending_idx
Int64Index([3, 2, 1], dtype='int64')
>>> ascending_idx.equals(descending_idx)
False
```

The dtype is *not* compared

```
>>> int64_idx = pd.Int64Index([1, 2, 3])
>>> int64_idx
Int64Index([1, 2, 3], dtype='int64')
>>> uint64_idx = pd.UInt64Index([1, 2, 3])
>>> uint64_idx
UInt64Index([1, 2, 3], dtype='uint64')
>>> int64_idx.equals(uint64_idx)
True
```

pandas.Index.factorize

Index.**factorize**(*sort=False*, *na_sentinel=- 1*)

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. *factorize* is available as both a top-level function *pandas.factorize()*, and as a method *Series.factorize()* and *Index.factorize()*.

Parameters

sort [bool, default False] Sort *uniques* and shuffle *codes* to maintain the relationship.

na_sentinel [int or None, default -1] Value to mark "not found". If None, will not drop the NaN from the uniques of the values.

Changed in version 1.1.2.

Returns

codes [ndarray] An integer ndarray that's an indexer into *uniques*. `uniques.take(codes)` will have the same values as *values*.

uniques [ndarray, Index, or Categorical] The unique valid values. When *values* is Categorical, *uniques* is a Categorical. When *values* is some other pandas object, an *Index* is returned. Otherwise, a 1-D ndarray is returned.

Note: Even if there's a missing value in *values*, *uniques* will *not* contain an entry for it.

See also:

cut Discretize continuous-valued array.

unique Find the unique value in an array.

Examples

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like *Series.factorize()*.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the *uniques* will be sorted, and *codes* will be shuffled so that the relationship is the maintained.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1]...)
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in *codes* with *na_sentinel* (`-1` by default). Note that missing values are never included in *uniques*.

```
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1,  1,  2,  0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we've only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of *uniques* will differ. For Categoricals, a *Categorical* is returned.

```
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
['a', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Notice that `'b'` is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
Index(['a', 'c'], dtype='object')
```

If NaN is in the values, and we want to include NaN in the uniques of the values, it can be achieved by setting `na_sentinel=None`.

```
>>> values = np.array([1, 2, 1, np.nan])
>>> codes, uniques = pd.factorize(values)  # default: na_sentinel=-1
>>> codes
array([ 0,  1,  0, -1])
>>> uniques
array([1., 2.])
```

```
>>> codes, uniques = pd.factorize(values, na_sentinel=None)
>>> codes
array([0, 1, 0, 2])
>>> uniques
array([ 1.,  2., nan])
```

pandas.Index.fillna

Index.**fillna**(*value=None*, *downcast=None*)

Fill NA/NaN values with the specified value.

Parameters

value [scalar] Scalar value to use to fill holes (e.g. 0). This value cannot be a list-likes.

downcast [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

Returns

Index

See also:

DataFrame.fillna Fill NaN values of a DataFrame.

Series.fillna Fill NaN Values of a Series.

pandas.Index.format

Index.**format**(*name=False*, *formatter=None*, *na_rep='NaN'*)

Render a string representation of the Index.

pandas.Index.get_indexer

Index.**get_indexer**(*target*, *method=None*, *limit=None*, *tolerance=None*)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

Parameters

target [Index]

method [{None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}, optional]

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.

- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit [int, optional] Maximum number of consecutive labels in `target` to match for inexact matches.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

Returns

indexer [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1,  2, -1])
```

Notice that the return value is an array of locations in `index` and `x` is marked by -1, as it is not in `index`.

pandas.Index.get_indexer_for

`Index.`**`get_indexer_for`**(*target*, ***kwargs*)

Guaranteed return of an indexer even when non-unique.

This dispatches to get_indexer or get_indexer_non_unique as appropriate.

Returns

numpy.ndarray List of indices.

pandas.Index.get_indexer_non_unique

`Index.`**`get_indexer_non_unique`**(*target*)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

Parameters

target [Index]

Returns

indexer [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

missing [ndarray of int] An indexer into the target of the values not found. These correspond to the -1 in the indexer array.

pandas.Index.get_level_values

Index.**get_level_values**(*level*)

Return an Index of values for requested level.

This is primarily useful to get an individual level of values from a MultiIndex, but is provided on Index as well for compatibility.

Parameters

level [int or str] It is either the integer position or the name of the level.

Returns

Index Calling object, as there is only one level in the Index.

See also:

MultiIndex.get_level_values Get values for a level of a MultiIndex.

Notes

For Index, level should be 0, since there are no multiple levels.

Examples

```
>>> idx = pd.Index(list('abc'))
>>> idx
Index(['a', 'b', 'c'], dtype='object')
```

Get level values by supplying *level* as integer:

```
>>> idx.get_level_values(0)
Index(['a', 'b', 'c'], dtype='object')
```

pandas.Index.get_loc

Index.**get_loc**(*key*, *method=None*, *tolerance=None*)

Get integer location, slice or boolean mask for requested label.

Parameters

key [label]

method [{None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}, optional]

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

tolerance [int or float, optional] Maximum distance from index value for inexact matches. The value of the index at the matching location must satisfy the equation `abs(index[loc] - key) <= tolerance`.

Returns

loc [int if unique index, slice if monotonic index, else mask]

Examples

```
>>> unique_index = pd.Index(list('abc'))
>>> unique_index.get_loc('b')
1
```

```
>>> monotonic_index = pd.Index(list('abbc'))
>>> monotonic_index.get_loc('b')
slice(1, 3, None)
```

```
>>> non_monotonic_index = pd.Index(list('abcb'))
>>> non_monotonic_index.get_loc('b')
array([False,  True, False,  True])
```

pandas.Index.get_slice_bound

`Index.`**`get_slice_bound`**(*label*, *side*, *kind*)

Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters

label [object]

side [{'left', 'right'}]

kind [{'loc', 'getitem'} or None]

Returns

int Index of label.

pandas.Index.get_value

`Index.`**`get_value`**(*series*, *key*)

Fast lookup of value from 1-dimensional ndarray.

Only use this if you know what you're doing.

Returns

scalar or Series

pandas.Index.groupby

Index.**groupby**(*values*)

Group the index labels by a given array of values.

Parameters

values [array] Values used to determine the groups.

Returns

dict {group name -> group labels}

pandas.Index.holds_integer

Index.**holds_integer**()

Whether the type is an integer type.

pandas.Index.identical

Index.**identical**(*other*)

Similar to equals, but checks that object attributes and types are also equal.

Returns

bool If two Index objects have equal elements and same type True, otherwise False.

pandas.Index.insert

Index.**insert**(*loc*, *item*)

Make new Index inserting new item at location.

Follows Python list.append semantics for negative values.

Parameters

loc [int]

item [object]

Returns

new_index [Index]

pandas.Index.intersection

Index.**intersection**(*other*, *sort=False*)

Form the intersection of two Index objects.

This returns a new Index with elements common to the index and *other*.

Parameters

other [Index or array-like]

sort [False or None, default False] Whether to sort the resulting index.

- False : do not sort the result.

- None : sort the result, except when *self* and *other* are equal or when the values cannot be compared.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default from `True` to `False`, to match the behaviour of 0.23.4 and earlier.

Returns

intersection [Index]

Examples

```
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.intersection(idx2)
Int64Index([3, 4], dtype='int64')
```

pandas.Index.is_

`Index.`**`is_`**`(`*other*`)`

More flexible, faster check like `is` but that works through views.

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters

other [object] Other object to compare against.

Returns

bool True if both have same underlying data, False otherwise.

See also:

Index.identical Works like `Index.is_` but also checks metadata.

pandas.Index.is_boolean

`Index.`**`is_boolean`**`()`

Check if the Index only consists of booleans.

Returns

bool Whether or not the Index only consists of booleans.

See also:

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.

is_mixed Check if the Index holds data with mixed data types.

Examples

```
>>> idx = pd.Index([True, False, True])
>>> idx.is_boolean()
True
```

```
>>> idx = pd.Index(["True", "False", "True"])
>>> idx.is_boolean()
False
```

```
>>> idx = pd.Index([True, False, "True"])
>>> idx.is_boolean()
False
```

pandas.Index.is_categorical

Index.**is_categorical**()

Check if the Index holds categorical data.

Returns

bool True if the Index is categorical.

See also:

CategoricalIndex Index for categorical data.

is_boolean Check if the Index only consists of booleans.

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_interval Check if the Index holds Interval objects.

is_mixed Check if the Index holds data with mixed data types.

Examples

```
>>> idx = pd.Index(["Watermelon", "Orange", "Apple",
...                 "Watermelon"]).astype("category")
>>> idx.is_categorical()
True
```

```
>>> idx = pd.Index([1, 3, 5, 7])
>>> idx.is_categorical()
False
```

```
>>> s = pd.Series(["Peter", "Victor", "Elisabeth", "Mar"])
>>> s
0        Peter
1       Victor
2    Elisabeth
3          Mar
dtype: object
>>> s.index.is_categorical()
False
```

pandas.Index.is_floating

Index.**is_floating**()

Check if the Index is a floating type.

The Index may consist of only floats, NaNs, or a mix of floats, integers, or NaNs.

Returns

bool Whether or not the Index only consists of only consists of floats, NaNs, or a mix of floats, integers, or NaNs.

See also:

is_boolean Check if the Index only consists of booleans.

is_integer Check if the Index only consists of integers.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.

is_mixed Check if the Index holds data with mixed data types.

Examples

```
>>> idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> idx.is_floating()
True
```

```
>>> idx = pd.Index([1.0, 2.0, np.nan, 4.0])
>>> idx.is_floating()
True
```

```
>>> idx = pd.Index([1, 2, 3, 4, np.nan])
>>> idx.is_floating()
True
```

```
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx.is_floating()
False
```

pandas.Index.is_integer

Index.**is_integer**()

Check if the Index only consists of integers.

Returns

bool Whether or not the Index only consists of integers.

See also:

is_boolean Check if the Index only consists of booleans.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.

is_mixed Check if the Index holds data with mixed data types.

Examples

```
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx.is_integer()
True
```

```
>>> idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> idx.is_integer()
False
```

```
>>> idx = pd.Index(["Apple", "Mango", "Watermelon"])
>>> idx.is_integer()
False
```

pandas.Index.is_interval

Index.**is_interval**()

Check if the Index holds Interval objects.

Returns

bool Whether or not the Index holds Interval objects.

See also:

IntervalIndex Index for Interval objects.

is_boolean Check if the Index only consists of booleans.

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_mixed Check if the Index holds data with mixed data types.

Examples

```
>>> idx = pd.Index([pd.Interval(left=0, right=5),
...                 pd.Interval(left=5, right=10)])
>>> idx.is_interval()
True
```

```
>>> idx = pd.Index([1, 3, 5, 7])
>>> idx.is_interval()
False
```

pandas.Index.is_mixed

Index.**is_mixed**()

Check if the Index holds data with mixed data types.

Returns

bool Whether or not the Index holds data with mixed data types.

See also:

is_boolean Check if the Index only consists of booleans.

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.

Examples

```
>>> idx = pd.Index(['a', np.nan, 'b'])
>>> idx.is_mixed()
True
```

```
>>> idx = pd.Index([1.0, 2.0, 3.0, 5.0])
>>> idx.is_mixed()
False
```

pandas.Index.is_numeric

Index.**is_numeric**()

Check if the Index only consists of numeric data.

Returns

bool Whether or not the Index only consists of numeric data.

See also:

is_boolean Check if the Index only consists of booleans.

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.

is_mixed Check if the Index holds data with mixed data types.

Examples

```
>>> idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> idx.is_numeric()
True
```

```
>>> idx = pd.Index([1, 2, 3, 4.0])
>>> idx.is_numeric()
True
```

```
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx.is_numeric()
True
```

```
>>> idx = pd.Index([1, 2, 3, 4.0, np.nan])
>>> idx.is_numeric()
True
```

```
>>> idx = pd.Index([1, 2, 3, 4.0, np.nan, "Apple"])
>>> idx.is_numeric()
False
```

pandas.Index.is_object

Index.**is_object**()

Check if the Index is of the object dtype.

Returns

bool Whether or not the Index is of the object dtype.

See also:

is_boolean Check if the Index only consists of booleans.

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.

is_mixed Check if the Index holds data with mixed data types.

Examples

```
>>> idx = pd.Index(["Apple", "Mango", "Watermelon"])
>>> idx.is_object()
True
```

```
>>> idx = pd.Index(["Apple", "Mango", 2.0])
>>> idx.is_object()
True
```

```
>>> idx = pd.Index(["Watermelon", "Orange", "Apple",
...                 "Watermelon"]).astype("category")
>>> idx.is_object()
False
```

```
>>> idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> idx.is_object()
False
```

pandas.Index.is_type_compatible

Index.**is_type_compatible**(*kind*)

Whether the index type is compatible with the provided type.

pandas.Index.isin

Index.**isin**(*values*, *level=None*)

Return a boolean array where the index values are in *values*.

Compute boolean array of whether each index value is found in the passed set of values. The length of the returned boolean array matches the length of the index.

Parameters

values [set or list-like] Sought values.

level [str or int, optional] Name or position of the index level to use (if the index is a *MultiIndex*).

Returns

is_contained [ndarray] NumPy array of boolean values.

See also:

Series.isin Same for Series.

DataFrame.isin Same method for DataFrames.

Notes

In the case of *MultiIndex* you must either specify *values* as a list-like object containing tuples that are the same length as the number of levels, or specify *level*. Otherwise it will raise a `ValueError`.

If *level* is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

Examples

```
>>> idx = pd.Index([1,2,3])
>>> idx
Int64Index([1, 2, 3], dtype='int64')
```

Check whether each index value in a list of values.

```
>>> idx.isin([1, 4])
array([ True, False, False])
```

```
>>> midx = pd.MultiIndex.from_arrays([[1,2,3],
...                                   ['red', 'blue', 'green']],
...                                   names=('number', 'color'))
>>> midx
MultiIndex([(1,   'red'),
            (2,  'blue'),
            (3, 'green')],
           names=['number', 'color'])
```

Check whether the strings in the 'color' level of the MultiIndex are in a list of colors.

```
>>> midx.isin(['red', 'orange', 'yellow'], level='color')
array([ True, False, False])
```

To check across the levels of a MultiIndex, pass a list of tuples:

```
>>> midx.isin([(1, 'red'), (3, 'red')])
array([ True, False, False])
```

For a DatetimeIndex, string values in *values* are converted to Timestamps.

```
>>> dates = ['2000-03-11', '2000-03-12', '2000-03-13']
>>> dti = pd.to_datetime(dates)
>>> dti
DatetimeIndex(['2000-03-11', '2000-03-12', '2000-03-13'],
dtype='datetime64[ns]', freq=None)
```

```
>>> dti.isin(['2000-03-11'])
array([ True, False, False])
```

pandas.Index.isna

Index.**isna**()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as `None`, `numpy.NaN` or `pd.NaT`, get mapped to `True` values. Everything else get mapped to `False` values. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

Returns

numpy.ndarray A boolean array of whether my values are NA.

See also:

Index.notna Boolean inverse of isna.

Index.dropna Omit entries with missing values.

isna Top-level isna.

Series.isna Detect missing values in Series object.

Examples

Show which entries in a pandas.Index are NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.isna()
array([False, False,  True])
```

Empty strings are not considered NA values. None is considered an NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.isna()
array([False, False, False,  True])
```

For datetimes, *NaT* (Not a Time) is considered as an NA value.

```
>>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),
...                         pd.Timestamp(''), None, pd.NaT])
>>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
              dtype='datetime64[ns]', freq=None)
>>> idx.isna()
array([False,  True,  True,  True])
```

pandas.Index.isnull

Index.**isnull**()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as `None`, `numpy.NaN` or `pd.NaT`, get mapped to `True` values. Everything else get mapped to `False` values. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

Returns

numpy.ndarray A boolean array of whether my values are NA.

See also:

Index.notna Boolean inverse of isna.

Index.dropna Omit entries with missing values.

isna Top-level isna.

Series.isna Detect missing values in Series object.

Examples

Show which entries in a pandas.Index are NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.isna()
array([False, False,  True])
```

Empty strings are not considered NA values. None is considered an NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.isna()
array([False, False, False,  True])
```

For datetimes, *NaT* (Not a Time) is considered as an NA value.

```
>>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),
...                         pd.Timestamp(''), None, pd.NaT])
>>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
              dtype='datetime64[ns]', freq=None)
>>> idx.isna()
array([False,  True,  True,  True])
```

pandas.Index.item

Index.**item**()

Return the first element of the underlying data as a Python scalar.

Returns

scalar The first element of %(klass)s.

Raises

ValueError If the data is not length-1.

pandas.Index.join

Index.**join**(*other*, *how='left'*, *level=None*, *return_indexers=False*, *sort=False*)

Compute join_index and indexers to conform data structures to the new index.

Parameters

other [Index]

how [{'left', 'right', 'inner', 'outer'}]

level [int or level name, default None]

return_indexers [bool, default False]

sort [bool, default False] Sort the join keys lexicographically in the result Index. If False, the order of the join keys depends on the join type (how keyword).

Returns

join_index, (left_indexer, right_indexer)

pandas.Index.map

Index.**map**(*mapper*, *na_action=None*)

Map values using input correspondence (a dict, Series, or function).

Parameters

mapper [function, dict, or Series] Mapping correspondence.

na_action [{None, 'ignore'}] If 'ignore', propagate NA values, without passing them to the mapping correspondence.

Returns

applied [Union[Index, MultiIndex], inferred] The output of the mapping function applied to the index. If the function returns a tuple with more than one element a MultiIndex will be returned.

pandas.Index.max

Index.**max**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return the maximum value of the Index.

Parameters

axis [int, optional] For compatibility with NumPy. Only 0 or None are allowed.

skipna [bool, default True] Exclude NA/null values when showing the result.

***args, **kwargs** Additional arguments and keywords for compatibility with NumPy.

Returns

scalar Maximum value.

See also:

Index.min Return the minimum value in an Index.

Series.max Return the maximum value in a Series.

DataFrame.max Return the maximum values in a DataFrame.

Examples

```
>>> idx = pd.Index([3, 2, 1])
>>> idx.max()
3
```

```
>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.max()
'c'
```

For a MultiIndex, the maximum is determined lexicographically.

```
>>> idx = pd.MultiIndex.from_product([('a', 'b'), (2, 1)])
>>> idx.max()
('b', 2)
```

pandas.Index.memory_usage

Index.**memory_usage**(*deep=False*)

Memory usage of the values.

Parameters

deep [bool, default False] Introspect the data deeply, interrogate *object* dtypes for system-level memory consumption.

Returns

bytes used

See also:

`numpy.ndarray.nbytes` Total bytes consumed by the elements of the array.

Notes

Memory usage does not include memory consumed by elements that are not components of the array if deep=False or if used on PyPy

pandas.Index.min

Index.**min**(*axis=None*, *skipna=True*, **args*, ***kwargs*)

Return the minimum value of the Index.

Parameters

axis [{None}] Dummy argument for consistency with Series.

skipna [bool, default True] Exclude NA/null values when showing the result.

***args, **kwargs** Additional arguments and keywords for compatibility with NumPy.

Returns

scalar Minimum value.

See also:

`Index.max` Return the maximum value of the object.

`Series.min` Return the minimum value in a Series.

`DataFrame.min` Return the minimum values in a DataFrame.

Examples

```
>>> idx = pd.Index([3, 2, 1])
>>> idx.min()
1
```

```
>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.min()
'a'
```

For a MultiIndex, the minimum is determined lexicographically.

```
>>> idx = pd.MultiIndex.from_product([('a', 'b'), (2, 1)])
>>> idx.min()
('a', 1)
```

pandas.Index.notna

Index.**notna**()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to `True`. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or `numpy.NaN`, get mapped to `False` values.

Returns

numpy.ndarray Boolean array to indicate which entries are not NA.

See also:

Index.notnull Alias of notna.

Index.isna Inverse of notna.

notna Top-level notna.

Examples

Show which entries in an Index are not NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([ True,  True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([ True,  True,  True, False])
```

pandas.Index.notnull

Index.**notnull**()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to `True`. Characters such as empty strings `''` or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or `numpy.NaN`, get mapped to `False` values.

Returns

numpy.ndarray Boolean array to indicate which entries are not NA.

See also:

Index.notnull Alias of notna.

Index.isna Inverse of notna.

notna Top-level notna.

Examples

Show which entries in an Index are not NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([ True,  True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([ True,  True,  True, False])
```

pandas.Index.nunique

Index.**nunique**(*dropna=True*)

Return number of unique elements in the object.

Excludes NA values by default.

Parameters

dropna [bool, default True] Don't include NaN in the count.

Returns

int

See also:

DataFrame.nunique Method nunique for DataFrame.

Series.count Count non-NA/null observations in the Series.

Examples

```
>>> s = pd.Series([1, 3, 5, 7, 7])
>>> s
0    1
1    3
2    5
3    7
4    7
dtype: int64
```

```
>>> s.nunique()
4
```

pandas.Index.putmask

Index.**putmask**(*mask*, *value*)

Return a new Index of the values set with the mask.

Returns

Index

See also:

numpy.ndarray.putmask Changes elements of an array based on conditional and input values.

pandas.Index.ravel

Index.**ravel**(*order='C'*)

Return an ndarray of the flattened values of the underlying data.

Returns

numpy.ndarray Flattened array.

See also:

numpy.ndarray.ravel Return a flattened array.

pandas.Index.reindex

Index.**reindex**(*target*, *method=None*, *level=None*, *limit=None*, *tolerance=None*)

Create index with target's values.

Parameters

target [an iterable]

Returns

new_index [pd.Index] Resulting index.

indexer [np.ndarray or None] Indices of output values in original index.

pandas.Index.rename

Index.**rename**(*name*, *inplace=False*)

Alter Index or MultiIndex name.

Able to set new names without level. Defaults to returning new index. Length of names must match number of levels in MultiIndex.

Parameters

name [label or list of labels] Name(s) to set.

inplace [bool, default False] Modifies the object directly, instead of creating a new Index or MultiIndex.

Returns

Index or None The same type as the caller or None if `inplace=True`.

See also:

Index.set_names Able to set new names partially and by level.

Examples

```
>>> idx = pd.Index(['A', 'C', 'A', 'B'], name='score')
>>> idx.rename('grade')
Index(['A', 'C', 'A', 'B'], dtype='object', name='grade')
```

```
>>> idx = pd.MultiIndex.from_product([['python', 'cobra'],
...                                   [2018, 2019]],
...                                   names=['kind', 'year'])
>>> idx
MultiIndex([('python', 2018),
            ('python', 2019),
            ( 'cobra', 2018),
            ( 'cobra', 2019)],
           names=['kind', 'year'])
>>> idx.rename(['species', 'year'])
MultiIndex([('python', 2018),
            ('python', 2019),
            ( 'cobra', 2018),
            ( 'cobra', 2019)],
           names=['species', 'year'])
>>> idx.rename('species')
Traceback (most recent call last):
TypeError: Must pass list-like as `names`.
```

pandas.Index.repeat

Index.**repeat**(*repeats*, *axis=None*)

Repeat elements of a Index.

Returns a new Index where each element of the current Index is repeated consecutively a given number of times.

Parameters

repeats [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty Index.

axis [None] Must be `None`. Has no effect but is accepted for compatibility with numpy.

Returns

repeated_index [Index] Newly created Index with repeated elements.

See also:

Series.repeat Equivalent function for Series.

numpy.repeat Similar method for `numpy.ndarray`.

Examples

```
>>> idx = pd.Index(['a', 'b', 'c'])
>>> idx
Index(['a', 'b', 'c'], dtype='object')
>>> idx.repeat(2)
Index(['a', 'a', 'b', 'b', 'c', 'c'], dtype='object')
>>> idx.repeat([1, 2, 3])
Index(['a', 'b', 'b', 'c', 'c', 'c'], dtype='object')
```

pandas.Index.searchsorted

Index.**searchsorted**(*value*, *side='left'*, *sorter=None*)

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Index *self* such that, if the corresponding elements in *value* were inserted before the indices, the order of *self* would be preserved.

Note: The Index *must* be monotonically sorted, otherwise wrong locations will likely be returned. Pandas does *not* check this for you.

Parameters

value [array_like] Values to insert into *self*.

side [{'left', 'right'}, optional] If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *self*).

sorter [1-D array_like, optional] Optional array of integer indices that sort *self* into ascending order. They are typically the result of `np.argsort`.

Returns

int or array of int A scalar or array of insertion points with the same shape as *value*.

Changed in version 0.24.0: If *value* is a scalar, an int is now always returned. Previously, scalar inputs returned an 1-item array for *Series* and *Categorical*.

See also:

sort_values Sort by the values along either axis.

numpy.searchsorted Similar method from NumPy.

Notes

Binary search is used to find the required insertion points.

Examples

```
>>> ser = pd.Series([1, 2, 3])
>>> ser
0    1
1    2
2    3
dtype: int64
```

```
>>> ser.searchsorted(4)
3
```

```
>>> ser.searchsorted([0, 4])
array([0, 3])
```

```
>>> ser.searchsorted([1, 3], side='left')
array([0, 2])
```

```
>>> ser.searchsorted([1, 3], side='right')
array([1, 3])
```

```
>>> ser = pd.Series(pd.to_datetime(['3/11/2000', '3/12/2000', '3/13/2000']))
>>> ser
0   2000-03-11
1   2000-03-12
2   2000-03-13
dtype: datetime64[ns]
```

```
>>> ser.searchsorted('3/14/2000')
3
```

```
>>> ser = pd.Categorical(
...     ['apple', 'bread', 'bread', 'cheese', 'milk'], ordered=True
... )
>>> ser
['apple', 'bread', 'bread', 'cheese', 'milk']
Categories (4, object): ['apple' < 'bread' < 'cheese' < 'milk']
```

```
>>> ser.searchsorted('bread')
1
```

```
>>> ser.searchsorted(['bread'], side='right')
array([3])
```

If the values are not monotonically sorted, wrong locations may be returned:

```
>>> ser = pd.Series([2, 1, 3])
>>> ser
0    2
```

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```
1    1
2    3
dtype: int64
```

```
>>> ser.searchsorted(1)
0  # wrong result, correct would be 1
```

pandas.Index.set_names

Index.**set_names**(*names*, *level=None*, *inplace=False*)

Set Index or MultiIndex name.

Able to set new names partially and by level.

Parameters

names [label or list of label] Name(s) to set.

level [int, label or list of int or label, optional] If the index is a MultiIndex, level(s) to set (None for all levels). Otherwise level must be None.

inplace [bool, default False] Modifies the object directly, instead of creating a new Index or MultiIndex.

Returns

Index or None The same type as the caller or None if `inplace=True`.

See also:

Index.rename Able to set new names without level.

Examples

```
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx.set_names('quarter')
Int64Index([1, 2, 3, 4], dtype='int64', name='quarter')
```

```
>>> idx = pd.MultiIndex.from_product([['python', 'cobra'],
...                                   [2018, 2019]])
>>> idx
MultiIndex([('python', 2018),
            ('python', 2019),
            ( 'cobra', 2018),
            ( 'cobra', 2019)],
           )
>>> idx.set_names(['kind', 'year'], inplace=True)
>>> idx
MultiIndex([('python', 2018),
            ('python', 2019),
            ( 'cobra', 2018),
            ( 'cobra', 2019)],
           names=['kind', 'year'])
```

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```
>>> idx.set_names('species', level=0)
MultiIndex([('python', 2018),
            ('python', 2019),
            ( 'cobra', 2018),
            ( 'cobra', 2019)],
           names=['species', 'year'])
```

pandas.Index.set_value

Index.**set_value**(*arr*, *key*, *value*)

Fast lookup of value from 1-dimensional ndarray.

Deprecated since version 1.0.

Notes

Only use this if you know what you're doing.

pandas.Index.shift

Index.**shift**(*periods=1*, *freq=None*)

Shift index by desired number of time frequency increments.

This method is for shifting the values of datetime-like indexes by a specified time increment a given number of times.

Parameters

periods [int, default 1] Number of periods (or increments) to shift by, can be positive or negative.

freq [pandas.DateOffset, pandas.Timedelta or str, optional] Frequency increment to shift by. If None, the index is shifted by its own *freq* attribute. Offset aliases are valid strings, e.g., 'D', 'W', 'M' etc.

Returns

pandas.Index Shifted index.

See also:

Series.shift Shift values of Series.

Notes

This method is only implemented for datetime-like index classes, i.e., DatetimeIndex, PeriodIndex and TimedeltaIndex.

Examples

Put the first 5 month starts of 2011 into an index.

```
>>> month_starts = pd.date_range('1/1/2011', periods=5, freq='MS')
>>> month_starts
DatetimeIndex(['2011-01-01', '2011-02-01', '2011-03-01', '2011-04-01',
               '2011-05-01'],
              dtype='datetime64[ns]', freq='MS')
```

Shift the index by 10 days.

```
>>> month_starts.shift(10, freq='D')
DatetimeIndex(['2011-01-11', '2011-02-11', '2011-03-11', '2011-04-11',
               '2011-05-11'],
              dtype='datetime64[ns]', freq=None)
```

The default value of *freq* is the *freq* attribute of the index, which is 'MS' (month start) in this example.

```
>>> month_starts.shift(10)
DatetimeIndex(['2011-11-01', '2011-12-01', '2012-01-01', '2012-02-01',
               '2012-03-01'],
              dtype='datetime64[ns]', freq='MS')
```

pandas.Index.slice_indexer

Index.**slice_indexer**(*start=None*, *end=None*, *step=None*, *kind=None*)

Compute the slice indexer for input labels and step.

Index needs to be ordered and unique.

Parameters

start [label, default None] If None, defaults to the beginning.

end [label, default None] If None, defaults to the end.

step [int, default None]

kind [str, default None]

Returns

indexer [slice]

Raises

KeyError [If key does not exist, or key is not unique and index is] not ordered.

Notes

This function assumes that the data is sorted, so use at your own peril

Examples

This is a method on all index types. For example you can do:

```
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_indexer(start='b', end='c')
slice(1, 3, None)
```

```
>>> idx = pd.MultiIndex.from_arrays([list('abcd'), list('efgh')])
>>> idx.slice_indexer(start='b', end=('c', 'g'))
slice(1, 3, None)
```

pandas.Index.slice_locs

Index.**slice_locs**(*start=None*, *end=None*, *step=None*, *kind=None*)

Compute slice locations for input labels.

Parameters

start [label, default None] If None, defaults to the beginning.

end [label, default None] If None, defaults to the end.

step [int, defaults None] If None, defaults to 1.

kind [{'loc', 'getitem'} or None]

Returns

start, end [int]

See also:

Index.get_loc Get location for a single label.

Notes

This method only works if the index is monotonic or unique.

Examples

```
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_locs(start='b', end='c')
(1, 3)
```

pandas.Index.sort

Index.**sort**(**args*, ***kwargs*)
Use sort_values instead.

pandas.Index.sort_values

Index.**sort_values**(*return_indexer=False*, *ascending=True*, *na_position='last'*, *key=None*)
Return a sorted copy of the index.

Return a sorted copy of the index, and optionally return the indices that sorted the index itself.

Parameters

return_indexer [bool, default False] Should the indices that would sort the index be returned.

ascending [bool, default True] Should the index values be sorted in an ascending order.

na_position [{'first' or 'last'}, default 'last'] Argument 'first' puts NaNs at the beginning, 'last' puts NaNs at the end.

New in version 1.2.0.

key [callable, optional] If not None, apply the key function to the index values before sorting. This is similar to the *key* argument in the builtin `sorted()` function, with the notable difference that this *key* function should be *vectorized*. It should expect an `Index` and return an `Index` of the same shape.

New in version 1.1.0.

Returns

sorted_index [pandas.Index] Sorted copy of the index.

indexer [numpy.ndarray, optional] The indices that the index itself was sorted by.

See also:

Series.sort_values Sort values of a Series.

DataFrame.sort_values Sort values in a DataFrame.

Examples

```
>>> idx = pd.Index([10, 100, 1, 1000])
>>> idx
Int64Index([10, 100, 1, 1000], dtype='int64')
```

Sort values in ascending order (default behavior).

```
>>> idx.sort_values()
Int64Index([1, 10, 100, 1000], dtype='int64')
```

Sort values in descending order, and also get the indices *idx* was sorted by.

```
>>> idx.sort_values(ascending=False, return_indexer=True)
(Int64Index([1000, 100, 10, 1], dtype='int64'), array([3, 1, 0, 2]))
```

pandas.Index.sortlevel

Index.**sortlevel**(*level=None*, *ascending=True*, *sort_remaining=None*)

For internal compatibility with the Index API.

Sort the Index. This is for compat with MultiIndex

Parameters

ascending [bool, default True] False to sort in descending order

level, sort_remaining are compat parameters

Returns

Index

pandas.Index.str

Index.**str**()

Vectorized string functions for Series and Index.

NAs stay NA unless handled otherwise by a particular method. Patterned after Python's string methods, with some inspiration from R's stringr package.

Examples

```
>>> s = pd.Series(["A_Str_Series"])
>>> s
0    A_Str_Series
dtype: object
```

```
>>> s.str.split("_")
0    [A, Str, Series]
dtype: object
```

```
>>> s.str.replace("_", "")
0    AStrSeries
dtype: object
```

pandas.Index.symmetric_difference

Index.**symmetric_difference**(*other*, *result_name=None*, *sort=None*)

Compute the symmetric difference of two Index objects.

Parameters

other [Index or array-like]

result_name [str]

sort [False or None, default None] Whether to sort the resulting index. By default, the values are attempted to be sorted, but any TypeError from incomparable elements is caught by pandas.

- None : Attempt to sort the result, but catch any TypeErrors from comparing incomparable elements.
- False : Do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from `True` to `None` (without change in behaviour).

Returns

symmetric_difference [Index]

Notes

`symmetric_difference` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `idx1.difference(idx2) | idx2.difference(idx1)` with duplicates dropped.

Examples

```
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([2, 3, 4, 5])
>>> idx1.symmetric_difference(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.Index.take

`Index.`**`take`**(*indices*, *axis=0*, *allow_fill=True*, *fill_value=None*, ***kwargs*)

Return a new Index of the values selected by the indices.

For internal compatibility with numpy arrays.

Parameters

indices [list] Indices to be taken.

axis [int, optional] The axis over which to select values, always 0.

allow_fill [bool, default True]

fill_value [bool, default None] If allow_fill=True and fill_value is not None, indices specified by -1 is regarded as NA. If Index doesn't hold NA, raise ValueError.

Returns

numpy.ndarray Elements of given indices.

See also:

`numpy.ndarray.take` Return an array formed from the elements of a at the given indices.

pandas.Index.to_flat_index

Index.**to_flat_index**()

Identity method.

New in version 0.24.0.

This is implemented for compatibility with subclass implementations when chaining.

Returns

pd.Index Caller.

See also:

MultiIndex.to_flat_index Subclass implementation.

pandas.Index.to_frame

Index.**to_frame**(*index=True*, *name=None*)

Create a DataFrame with a column containing the Index.

New in version 0.24.0.

Parameters

index [bool, default True] Set the index of the returned DataFrame as the original Index.

name [object, default None] The passed name should substitute for the index name (if it has one).

Returns

DataFrame DataFrame containing the original Index data.

See also:

Index.to_series Convert an Index to a Series.

Series.to_frame Convert Series to DataFrame.

Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
       animal
animal
Ant       Ant
Bear     Bear
Cow       Cow
```

By default, the original Index is reused. To enforce a new Index:

```
>>> idx.to_frame(index=False)
    animal
0   Ant
1  Bear
2   Cow
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_frame(index=False, name='zoo')
    zoo
0   Ant
1  Bear
2   Cow
```

pandas.Index.to_list

Index.**to_list**()

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns

list

See also:

numpy.ndarray.tolist Return the array as an a.ndim-levels deep nested list of Python scalars.

pandas.Index.to_native_types

Index.**to_native_types**(*slicer=None*, ***kwargs*)

Format specified values of *self* and return them.

Deprecated since version 1.2.0.

Parameters

slicer [int, array-like] An indexer into *self* that specifies which values are used in the formatting process.

kwargs [dict] Options for specifying how the values should be formatted. These options include the following:

1) **na_rep** [str] The value that serves as a placeholder for NULL values
2) **quoting** [bool or None] Whether or not there are quoted values in *self*
3) **date_format** [str] The format used to represent date-like values.

Returns

numpy.ndarray Formatted values.

pandas.Index.to_numpy

Index.**to_numpy**(*dtype=None*, *copy=False*, *na_value=<object object>*, ***kwargs*)

A NumPy ndarray representing the values in this Series or Index.

New in version 0.24.0.

Parameters

dtype [str or numpy.dtype, optional] The dtype to pass to `numpy.asarray()`.

copy [bool, default False] Whether to ensure that the returned value is not a view on another array. Note that `copy=False` does not *ensure* that `to_numpy()` is no-copy. Rather, `copy=True` ensure that a copy is made, even if not strictly necessary.

na_value [Any, optional] The value to use for missing values. The default value depends on *dtype* and the type of the array.

New in version 1.0.0.

****kwargs** Additional keywords passed through to the `to_numpy` method of the underlying array (for extension arrays).

New in version 1.0.0.

Returns

numpy.ndarray

See also:

Series.array Get the actual data stored within.

Index.array Get the actual data stored within.

DataFrame.to_numpy Similar method for DataFrame.

Notes

The returned array will be the same up to equality (values equal in *self* will be equal in the returned array; likewise for values that are not equal). When *self* contains an ExtensionArray, the dtype may be different. For example, for a category-dtype Series, `to_numpy()` will return a NumPy array and the categorical dtype will be lost.

For NumPy dtypes, this will be a reference to the actual data stored in this Series or Index (assuming `copy=False`). Modifying the result in place will modify the data stored in the Series or Index (not that we recommend doing that).

For extension types, `to_numpy()` *may* require copying data and coercing the result to a NumPy type (possibly object), which may be expensive. When you need a no-copy reference to the underlying data, *Series.array* should be used instead.

This table lays out the different dtypes and default return types of `to_numpy()` for various dtypes within pandas.

dtype	array type
category[T]	ndarray[T] (same dtype as input)
period	ndarray[object] (Periods)
interval	ndarray[object] (Intervals)
IntegerNA	ndarray[object]
datetime64[ns]	datetime64[ns]
datetime64[ns, tz]	ndarray[object] (Timestamps)

Examples

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.to_numpy()
array(['a', 'b', 'a'], dtype=object)
```

Specify the *dtype* to control how datetime-aware data is represented. Use `dtype=object` to return an ndarray of pandas *Timestamp* objects, each with the correct `tz`.

```
>>> ser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))
>>> ser.to_numpy(dtype=object)
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or `dtype='datetime64[ns]'` to return an ndarray of native datetime64 values. The values are converted to UTC and the timezone info is dropped.

```
>>> ser.to_numpy(dtype="datetime64[ns]")
...
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00...'],
      dtype='datetime64[ns]')
```

pandas.Index.to_series

Index.**to_series**(*index=None*, *name=None*)

Create a Series with both index and values equal to the index keys.

Useful with map for returning an indexer based on an index.

Parameters

index [Index, optional] Index of resulting Series. If None, defaults to original index.

name [str, optional] Name of resulting Series. If None, defaults to name of original index.

Returns

Series The dtype will be based on the type of the Index values.

See also:

Index.to_frame Convert an Index to a DataFrame.

Series.to_frame Convert Series to DataFrame.

Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
```

By default, the original Index and original name is reused.

```
>>> idx.to_series()
animal
Ant      Ant
Bear    Bear
Cow      Cow
Name: animal, dtype: object
```

To enforce a new Index, specify new labels to `index`:

```
>>> idx.to_series(index=[0, 1, 2])
0     Ant
1    Bear
2     Cow
Name: animal, dtype: object
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_series(name='zoo')
animal
Ant      Ant
Bear    Bear
Cow      Cow
Name: zoo, dtype: object
```

pandas.Index.tolist

Index.**tolist**()

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns

list

See also:

numpy.ndarray.tolist Return the array as an a.ndim-levels deep nested list of Python scalars.

pandas.Index.transpose

Index.**transpose**(**args*, ***kwargs*)

Return the transpose, which is by definition self.

Returns

%(klass)s

pandas.Index.union

Index.**union**(*other*, *sort=None*)

Form the union of two Index objects.

If the Index objects are incompatible, both Index objects will be cast to dtype('object') first.

Changed in version 0.25.0.

Parameters

other [Index or array-like]

sort [bool or None, default None] Whether to sort the resulting Index.

- None : Sort the result, except when
  1. *self* and *other* are equal.
  2. *self* or *other* has length 0.
  3. Some values in *self* or *other* cannot be compared. A RuntimeWarning is issued in this case.
- False : do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from `True` to `None` (without change in behaviour).

Returns

union [Index]

Examples

Union matching dtypes

```
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.union(idx2)
Int64Index([1, 2, 3, 4, 5, 6], dtype='int64')
```

Union mismatched dtypes

```
>>> idx1 = pd.Index(['a', 'b', 'c', 'd'])
>>> idx2 = pd.Index([1, 2, 3, 4])
>>> idx1.union(idx2)
Index(['a', 'b', 'c', 'd', 1, 2, 3, 4], dtype='object')
```

pandas.Index.unique

Index.**unique**(*level=None*)

Return unique values in the index.

Unique values are returned in order of appearance, this does NOT sort.

Parameters

level [int or str, optional, default None] Only return values from specified level (for MultiIndex).

Returns

Index without duplicates

See also:

unique Numpy array of unique values in that column.

Series.unique Return unique values of Series object.

pandas.Index.value_counts

Index.**value_counts**(*normalize=False*, *sort=True*, *ascending=False*, *bins=None*, *dropna=True*)

Return a Series containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters

normalize [bool, default False] If True then the object returned will contain the relative frequencies of the unique values.

sort [bool, default True] Sort by frequencies.

ascending [bool, default False] Sort in ascending order.

bins [int, optional] Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data.

dropna [bool, default True] Don't include counts of NaN.

Returns

Series

See also:

Series.count Number of non-NA elements in a Series.

DataFrame.count Number of non-NA elements in a DataFrame.

DataFrame.value_counts Equivalent method on DataFrames.

Examples

```
>>> index = pd.Index([3, 1, 2, 3, 4, np.nan])
>>> index.value_counts()
3.0    2
2.0    1
4.0    1
1.0    1
dtype: int64
```

With *normalize* set to *True*, returns the relative frequency by dividing all values by the sum of values.

```
>>> s = pd.Series([3, 1, 2, 3, 4, np.nan])
>>> s.value_counts(normalize=True)
3.0    0.4
2.0    0.2
4.0    0.2
1.0    0.2
dtype: float64
```

bins

Bins can be useful for going from a continuous variable to a categorical variable; instead of counting unique apparitions of values, divide the index in the specified number of half-open bins.

```
>>> s.value_counts(bins=3)
(0.996, 2.0]    2
(2.0, 3.0]      2
(3.0, 4.0]      1
dtype: int64
```

dropna

With *dropna* set to *False* we can also see NaN index values.

```
>>> s.value_counts(dropna=False)
3.0    2
2.0    1
NaN    1
4.0    1
1.0    1
dtype: int64
```

pandas.Index.where

Index.**where**(*cond*, *other=None*)

Replace values where the condition is False.

The replacement is taken from other.

Parameters

cond [bool array-like with the same length as self] Condition to select the values on.

other [scalar, or array-like, default None] Replacement if the condition is False.

Returns

pandas.Index A copy of self with values replaced from other where the condition is False.

See also:

Series.where Same method for Series.

DataFrame.where Same method for DataFrame.

Examples

```
>>> idx = pd.Index(['car', 'bike', 'train', 'tractor'])
>>> idx
Index(['car', 'bike', 'train', 'tractor'], dtype='object')
>>> idx.where(idx.isin(['car', 'train']), 'other')
Index(['car', 'other', 'train', 'other'], dtype='object')
```

view

Properties

Index.values	Return an array representing the data in the Index.
Index.is_monotonic	Alias for is_monotonic_increasing.
Index.is_monotonic_increasing	Return if the index is monotonic increasing (only equal or increasing) values.
Index.is_monotonic_decreasing	Return if the index is monotonic decreasing (only equal or decreasing) values.
Index.is_unique	Return if the index has unique values.
Index.has_duplicates	Check if the Index has duplicate values.
Index.hasnans	Return if I have any nans; enables various perf speedups.
Index.dtype	Return the dtype object of the underlying data.
Index.inferred_type	Return a string of the type inferred from the values.
Index.is_all_dates	Whether or not the index values only consist of dates.
Index.shape	Return a tuple of the shape of the underlying data.
Index.name	Return Index or MultiIndex name.
Index.names	
Index.nbytes	Return the number of bytes in the underlying data.
Index.ndim	Number of dimensions of the underlying data, by definition 1.
Index.size	Return the number of elements in the underlying data.
Index.empty	
Index.T	Return the transpose, which is by definition self.
Index.memory_usage([deep])	Memory usage of the values.

pandas.Index.names

property Index.**names**

pandas.Index.empty

property Index.**empty**

Modifying and computations

Index.all()	Return whether all elements are Truthy.
Index.any(*args, **kwargs)	Return whether any element is Truthy.
Index.argmin([axis, skipna])	Return int position of the smallest value in the Series.
Index.argmax([axis, skipna])	Return int position of the largest value in the Series.
Index.copy([name, deep, dtype, names])	Make a copy of this object.
Index.delete(loc)	Make new Index with passed location(-s) deleted.
Index.drop(labels[, errors])	Make new Index with passed list of labels deleted.
Index.drop_duplicates([keep])	Return Index with duplicate values removed.
Index.duplicated([keep])	Indicate duplicate index values.
Index.equals(other)	Determine if two Index object are equal.
Index.factorize([sort, na_sentinel])	Encode the object as an enumerated type or categorical variable.
Index.identical(other)	Similar to equals, but checks that object attributes and types are also equal.
Index.insert(loc, item)	Make new Index inserting new item at location.
*Index.is_*(other)	More flexible, faster check like `is` but that works through views.
Index.is_boolean()	Check if the Index only consists of booleans.
Index.is_categorical()	Check if the Index holds categorical data.
Index.is_floating()	Check if the Index is a floating type.
Index.is_integer()	Check if the Index only consists of integers.
Index.is_interval()	Check if the Index holds Interval objects.
Index.is_mixed()	Check if the Index holds data with mixed data types.
Index.is_numeric()	Check if the Index only consists of numeric data.
Index.is_object()	Check if the Index is of the object dtype.
Index.min([axis, skipna])	Return the minimum value of the Index.
Index.max([axis, skipna])	Return the maximum value of the Index.
Index.reindex(target[, method, level, ...])	Create index with target's values.
Index.rename(name[, inplace])	Alter Index or MultiIndex name.
Index.repeat(repeats[, axis])	Repeat elements of a Index.
Index.where(cond[, other])	Replace values where the condition is False.
Index.take(indices[, axis, allow_fill, ...])	Return a new Index of the values selected by the indices.
Index.putmask(mask, value)	Return a new Index of the values set with the mask.
Index.unique([level])	Return unique values in the index.
Index.nunique([dropna])	Return number of unique elements in the object.
Index.value_counts([normalize, sort, ...])	Return a Series containing counts of unique values.

Compatibility with MultiIndex

Index.set_names(names[, level, inplace])	Set Index or MultiIndex name.
Index.droplevel([level])	Return index with requested level(s) removed.

Missing values

Index.fillna([value, downcast])	Fill NA/NaN values with the specified value.
Index.dropna([how])	Return Index without NA/NaN values.
Index.isna()	Detect missing values.
Index.notna()	Detect existing (non-missing) values.

Conversion

Index.astype(dtype[, copy])	Create an Index with values cast to dtypes.
Index.item()	Return the first element of the underlying data as a Python scalar.
Index.map(mapper[, na_action])	Map values using input correspondence (a dict, Series, or function).
Index.ravel([order])	Return an ndarray of the flattened values of the underlying data.
Index.to_list()	Return a list of the values.
Index.to_native_types([slicer])	(DEPRECATED) Format specified values of *self* and return them.
Index.to_series([index, name])	Create a Series with both index and values equal to the index keys.
Index.to_frame([index, name])	Create a DataFrame with a column containing the Index.
Index.view([cls])	

pandas.Index.view

Index.**view**(*cls=None*)

Sorting

Index.argsort(*args, **kwargs)	Return the integer indices that would sort the index.
Index.searchsorted(value[, side, sorter])	Find indices where elements should be inserted to maintain order.
Index.sort_values([return_indexer, ...])	Return a sorted copy of the index.

Time-specific operations

Index.shift([periods, freq])	Shift index by desired number of time frequency increments.

Combining / joining / set operations

Index.append(other)	Append a collection of Index options together.
Index.join(other[, how, level, ...])	Compute join_index and indexers to conform data structures to the new index.
Index.intersection(other[, sort])	Form the intersection of two Index objects.
Index.union(other[, sort])	Form the union of two Index objects.
Index.difference(other[, sort])	Return a new Index with elements of index not in *other*.
Index.symmetric_difference(other[, ...])	Compute the symmetric difference of two Index objects.

Selecting

Index.asof(label)	Return the label from the index, or, if not present, the previous one.
Index.asof_locs(where, mask)	Return the locations (indices) of labels in the index.
Index.get_indexer(target[, method, limit, ...])	Compute indexer and mask for new index given the current index.
Index.get_indexer_for(target, **kwargs)	Guaranteed return of an indexer even when non-unique.
Index.get_indexer_non_unique(target)	Compute indexer and mask for new index given the current index.
Index.get_level_values(level)	Return an Index of values for requested level.
Index.get_loc(key[, method, tolerance])	Get integer location, slice or boolean mask for requested label.
Index.get_slice_bound(label, side, kind)	Calculate slice bound that corresponds to given label.
Index.get_value(series, key)	Fast lookup of value from 1-dimensional ndarray.
Index.isin(values[, level])	Return a boolean array where the index values are in *values*.
Index.slice_indexer([start, end, step, kind])	Compute the slice indexer for input labels and step.
Index.slice_locs([start, end, step, kind])	Compute slice locations for input labels.

3.6.2 Numeric Index

RangeIndex([start, stop, step, dtype, copy, ...])	Immutable Index implementing a monotonic integer range.
Int64Index([data, dtype, copy, name])	Immutable sequence used for indexing and alignment.
UInt64Index([data, dtype, copy, name])	Immutable sequence used for indexing and alignment.
Float64Index([data, dtype, copy, name])	Immutable sequence used for indexing and alignment.

pandas.RangeIndex

class pandas.**RangeIndex**(*start=None*, *stop=None*, *step=None*, *dtype=None*, *copy=False*, *name=None*)

Immutable Index implementing a monotonic integer range.

RangeIndex is a memory-saving special case of Int64Index limited to representing monotonic ranges. Using RangeIndex may in some instances improve computing speed.

This is the default index type used by DataFrame and Series when no explicit index is provided by the user.

Parameters

start [int (default: 0), or other RangeIndex instance] If int and "stop" is not given, interpreted as "stop" instead.

stop [int (default: 0)]

step [int (default: 1)]

dtype [np.int64] Unused, accepted for homogeneity with other index types.

copy [bool, default False] Unused, accepted for homogeneity with other index types.

name [object, optional] Name to be stored in the index.

See also:

Index The base pandas Index type.
Int64Index Index of int64 data.

Attributes

start	The value of the *start* parameter (0 if this was not supplied).
stop	The value of the *stop* parameter.
step	The value of the *step* parameter (1 if this was not supplied).

pandas.RangeIndex.start

RangeIndex.**start**

The value of the *start* parameter (0 if this was not supplied).

pandas.RangeIndex.stop

RangeIndex.**stop**
The value of the *stop* parameter.

pandas.RangeIndex.step

RangeIndex.**step**
The value of the *step* parameter (1 if this was not supplied).

Methods

from_range(data[, name, dtype])	Create RangeIndex from a range object.

pandas.RangeIndex.from_range

classmethod RangeIndex.**from_range**(*data*, *name=None*, *dtype=None*)
Create RangeIndex from a range object.

Returns

RangeIndex

pandas.Int64Index

class pandas.**Int64Index**(*data=None*, *dtype=None*, *copy=False*, *name=None*)
Immutable sequence used for indexing and alignment. The basic object storing axis labels for all pandas objects. Int64Index is a special case of *Index* with purely integer labels. .

Parameters

data [array-like (1-dimensional)]

dtype [NumPy dtype (default: int64)]

copy [bool] Make a copy of input ndarray.

name [object] Name to be stored in the index.

See also:

Index The base pandas Index type.

Notes

An Index instance can **only** contain hashable objects.

Attributes

None	

Methods

None	

pandas.UInt64Index

class pandas.**UInt64Index**(*data=None*, *dtype=None*, *copy=False*, *name=None*)

Immutable sequence used for indexing and alignment. The basic object storing axis labels for all pandas objects. UInt64Index is a special case of *Index* with purely unsigned integer labels. .

Parameters

data [array-like (1-dimensional)]

dtype [NumPy dtype (default: uint64)]

copy [bool] Make a copy of input ndarray.

name [object] Name to be stored in the index.

See also:

Index The base pandas Index type.

Notes

An Index instance can **only** contain hashable objects.

Attributes

None	

Methods

None	

pandas.Float64Index

class pandas.**Float64Index**(*data=None*, *dtype=None*, *copy=False*, *name=None*)

Immutable sequence used for indexing and alignment. The basic object storing axis labels for all pandas objects. Float64Index is a special case of *Index* with purely float labels. .

Parameters

data [array-like (1-dimensional)]

dtype [NumPy dtype (default: float64)]

copy [bool] Make a copy of input ndarray.

name [object] Name to be stored in the index.

See also:

Index The base pandas Index type.

Notes

An Index instance can **only** contain hashable objects.

Attributes

None	

Methods

None	

RangeIndex.start	The value of the *start* parameter (0 if this was not supplied).
RangeIndex.stop	The value of the *stop* parameter.
RangeIndex.step	The value of the *step* parameter (1 if this was not supplied).
RangeIndex.from_range(data[, name, dtype])	Create RangeIndex from a range object.

3.6.3 CategoricalIndex

CategoricalIndex([data, categories, ...])	Index based on an underlying *Categorical*.

pandas.CategoricalIndex

class pandas.**CategoricalIndex**(*data=None*, *categories=None*, *ordered=None*, *dtype=None*, *copy=False*, *name=None*)

Index based on an underlying *Categorical*.

CategoricalIndex, like Categorical, can only take on a limited, and usually fixed, number of possible values (*categories*). Also, like Categorical, it might have an order, but numerical operations (additions, divisions, ...) are not possible.

Parameters

data [array-like (1-dimensional)] The values of the categorical. If *categories* are given, values not in *categories* will be replaced with NaN.

categories [index-like, optional] The categories for the categorical. Items need to be unique. If the categories are not given here (and also not in *dtype*), they will be inferred from the *data*.

ordered [bool, optional] Whether or not this categorical is treated as an ordered categorical. If not given here or in *dtype*, the resulting categorical will be unordered.

dtype [CategoricalDtype or "category", optional] If *CategoricalDtype*, cannot be used together with *categories* or *ordered*.

copy [bool, default False] Make a copy of input ndarray.

name [object, optional] Name to be stored in the index.

Raises

ValueError If the categories do not validate.

TypeError If an explicit `ordered=True` is given but no *categories* and the *values* are not sortable.

See also:

Index The base pandas Index type.
Categorical A categorical array.
CategoricalDtype Type for categorical data.

Notes

See the user guide for more.

Examples

```
>>> pd.CategoricalIndex(["a", "b", "c", "a", "b", "c"])
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'],
                 categories=['a', 'b', 'c'], ordered=False, dtype='category')
```

`CategoricalIndex` can also be instantiated from a `Categorical`:

```
>>> c = pd.Categorical(["a", "b", "c", "a", "b", "c"])
>>> pd.CategoricalIndex(c)
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'],
                 categories=['a', 'b', 'c'], ordered=False, dtype='category')
```

Ordered `CategoricalIndex` can have a min and max value.

```
>>> ci = pd.CategoricalIndex(
...     ["a", "b", "c", "a", "b", "c"], ordered=True, categories=["c", "b", "a"]
... )
>>> ci
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'],
                 categories=['c', 'b', 'a'], ordered=True, dtype='category')
>>> ci.min()
'c'
```

Attributes

codes	The category codes of this categorical.
categories	The categories of this categorical.
ordered	Whether the categories have an ordered relationship.

pandas.CategoricalIndex.codes

property CategoricalIndex.**codes**

The category codes of this categorical.

Codes are an array of integers which are the positions of the actual values in the categories array.

There is no setter, use the other categorical methods and the normal item setter to change values in the categorical.

Returns

ndarray[int] A non-writable view of the *codes* array.

pandas.CategoricalIndex.categories

property CategoricalIndex.**categories**

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to *categories* is a inplace operation!

Raises

ValueError If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

See also:

rename_categories Rename categories.

reorder_categories Reorder categories.

add_categories Add new categories.

remove_categories Remove the specified categories.

remove_unused_categories Remove categories which are not used.

set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.ordered

property CategoricalIndex.**ordered**
Whether the categories have an ordered relationship.

Methods

rename_categories(*args, **kwargs)	Rename categories.
reorder_categories(*args, **kwargs)	Reorder categories as specified in new_categories.
add_categories(*args, **kwargs)	Add new categories.
remove_categories(*args, **kwargs)	Remove the specified categories.
remove_unused_categories(*args, **kwargs)	Remove categories which are not used.
set_categories(*args, **kwargs)	Set the categories to the specified new_categories.
as_ordered(*args, **kwargs)	Set the Categorical to be ordered.
as_unordered(*args, **kwargs)	Set the Categorical to be unordered.
map(mapper)	Map values using input correspondence (a dict, Series, or function).

pandas.CategoricalIndex.rename_categories

CategoricalIndex.**rename_categories**(**args*, ***kwargs*)
Rename categories.

Parameters

new_categories [list-like, dict-like or callable] New categories which will replace old categories.

- list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
- dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.
- callable : a callable that is called on all items in the old categories and whose return values comprise the new categories.

inplace [bool, default False] Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns

cat [Categorical or None] Categorical with removed categories or None if `inplace=True`.

Raises

ValueError If new categories are list-like and do not have the same number of items than the current categories or do not validate as categories

See also:

reorder_categories Reorder categories.

add_categories Add new categories.

remove_categories Remove the specified categories.

remove_unused_categories Remove categories which are not used.

set_categories Set the categories to the specified ones.

Examples

```
>>> c = pd.Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]
```

For dict-like `new_categories`, extra keys are ignored and categories not in the dictionary are passed through

```
>>> c.rename_categories({'a': 'A', 'c': 'C'})
['A', 'A', 'b']
Categories (2, object): ['A', 'b']
```

You may also provide a callable to create the new categories

```
>>> c.rename_categories(lambda x: x.upper())
['A', 'A', 'B']
Categories (2, object): ['A', 'B']
```

pandas.CategoricalIndex.reorder_categories

CategoricalIndex.**reorder_categories**(**args*, ***kwargs*)

Reorder categories as specified in new_categories.

new_categories need to include all old categories and no new category items.

Parameters

new_categories [Index-like] The categories in new order.

ordered [bool, optional] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace [bool, default False] Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns

cat [Categorical or None] Categorical with removed categories or None if `inplace=True`.

Raises

ValueError If the new categories do not contain all old category items or any new ones

See also:

rename_categories Rename categories.

add_categories Add new categories.

remove_categories Remove the specified categories.

remove_unused_categories Remove categories which are not used.

set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.add_categories

CategoricalIndex.**add_categories**(**args*, ***kwargs*)

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

Parameters

new_categories [category or list-like of category] The new categories to be included.

inplace [bool, default False] Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns

cat [Categorical or None] Categorical with new categories added or None if `inplace=True`.

Raises

ValueError If the new categories include old categories or do not validate as categories

See also:

rename_categories Rename categories.

reorder_categories Reorder categories.

remove_categories Remove the specified categories.

remove_unused_categories Remove categories which are not used.

set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.remove_categories

CategoricalIndex.**remove_categories**(**args*, ***kwargs*)

Remove the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters

removals [category or list of categories] The categories which should be removed.

inplace [bool, default False] Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns

cat [Categorical or None] Categorical with removed categories or None if `inplace=True`.

Raises

ValueError If the removals are not contained in the categories

See also:

rename_categories Rename categories.

reorder_categories Reorder categories.

add_categories Add new categories.

remove_unused_categories Remove categories which are not used.

set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.remove_unused_categories

CategoricalIndex.**remove_unused_categories**(**args*, ***kwargs*)

Remove categories which are not used.

Parameters

inplace [bool, default False] Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Deprecated since version 1.2.0.

Returns

cat [Categorical or None] Categorical with unused categories dropped or None if `inplace=True`.

See also:

rename_categories Rename categories.

reorder_categories Reorder categories.

add_categories Add new categories.

remove_categories Remove the specified categories.

set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.set_categories

CategoricalIndex.**set_categories**(**args*, ***kwargs*)

Set the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes, which does not considers a S1 string equal to a single char python string.

Parameters

new_categories [Index-like] The categories in new order.

ordered [bool, default False] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename [bool, default False] Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace [bool, default False] Whether or not to reorder the categories in-place or return a copy of this categorical with reordered categories.

Returns

Categorical with reordered categories or None if inplace.

Raises

ValueError If new_categories does not validate as categories

See also:

rename_categories Rename categories.

reorder_categories Reorder categories.

add_categories Add new categories.

remove_categories Remove the specified categories.

remove_unused_categories Remove categories which are not used.

pandas.CategoricalIndex.as_ordered

CategoricalIndex.**as_ordered**(**args*, ***kwargs*)

Set the Categorical to be ordered.

Parameters

inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to True.

Returns

Categorical or None Ordered Categorical or None if `inplace=True`.

pandas.CategoricalIndex.as_unordered

CategoricalIndex.**as_unordered**(**args*, ***kwargs*)

Set the Categorical to be unordered.

Parameters

inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to False.

Returns

Categorical or None Unordered Categorical or None if `inplace=True`.

pandas.CategoricalIndex.map

CategoricalIndex.**map**(*mapper*)

Map values using input correspondence (a dict, Series, or function).

Maps the values (their categories, not the codes) of the index to new categories. If the mapping correspondence is one-to-one the result is a *CategoricalIndex* which has the same order property as the original, otherwise an *Index* is returned.

If a *dict* or *Series* is used any unmapped category is mapped to *NaN*. Note that if this happens an *Index* will be returned.

Parameters

mapper [function, dict, or Series] Mapping correspondence.

Returns

pandas.CategoricalIndex or pandas.Index Mapped index.

See also:

Index.map Apply a mapping correspondence on an *Index*.

Series.map Apply a mapping correspondence on a *Series*.

Series.apply Apply more complex functions on a *Series*.

Examples

```
>>> idx = pd.CategoricalIndex(['a', 'b', 'c'])
>>> idx
CategoricalIndex(['a', 'b', 'c'], categories=['a', 'b', 'c'],
                 ordered=False, dtype='category')
>>> idx.map(lambda x: x.upper())
CategoricalIndex(['A', 'B', 'C'], categories=['A', 'B', 'C'],
                 ordered=False, dtype='category')
>>> idx.map({'a': 'first', 'b': 'second', 'c': 'third'})
CategoricalIndex(['first', 'second', 'third'], categories=['first',
                 'second', 'third'], ordered=False, dtype='category')
```

If the mapping is one-to-one the ordering of the categories is preserved:

```
>>> idx = pd.CategoricalIndex(['a', 'b', 'c'], ordered=True)
>>> idx
CategoricalIndex(['a', 'b', 'c'], categories=['a', 'b', 'c'],
                 ordered=True, dtype='category')
>>> idx.map({'a': 3, 'b': 2, 'c': 1})
CategoricalIndex([3, 2, 1], categories=[3, 2, 1], ordered=True,
                 dtype='category')
```

If the mapping is not one-to-one an *Index* is returned:

```
>>> idx.map({'a': 'first', 'b': 'second', 'c': 'first'})
Index(['first', 'second', 'first'], dtype='object')
```

If a *dict* is used, all unmapped categories are mapped to *NaN* and the result is an *Index*:

```
>>> idx.map({'a': 'first', 'b': 'second'})
Index(['first', 'second', nan], dtype='object')
```

Categorical components

CategoricalIndex.codes	The category codes of this categorical.
CategoricalIndex.categories	The categories of this categorical.
CategoricalIndex.ordered	Whether the categories have an ordered relationship.
CategoricalIndex.rename_categories(*args, ...)	Rename categories.
CategoricalIndex.reorder_categories(*args, ...)	Reorder categories as specified in new_categories.
CategoricalIndex.add_categories(*args, **kwargs)	Add new categories.
CategoricalIndex.remove_categories(*args, ...)	Remove the specified categories.
CategoricalIndex.remove_unused_categories(...)	Remove categories which are not used.
CategoricalIndex.set_categories(*args, **kwargs)	Set the categories to the specified new_categories.
CategoricalIndex.as_ordered(*args, **kwargs)	Set the Categorical to be ordered.
CategoricalIndex.as_unordered(*args, **kwargs)	Set the Categorical to be unordered.

Modifying and computations

CategoricalIndex.map(mapper)	Map values using input correspondence (a dict, Series, or function).
CategoricalIndex.equals(other)	Determine if two CategoricalIndex objects contain the same elements.

pandas.CategoricalIndex.equals

CategoricalIndex.**equals**(*other*)

Determine if two CategoricalIndex objects contain the same elements.

Returns

bool If two CategoricalIndex objects have equal elements True, otherwise False.

3.6.4 IntervalIndex

IntervalIndex(data[, closed, dtype, copy, ...])	Immutable index of intervals that are closed on the same side.

pandas.IntervalIndex

class pandas.**IntervalIndex**(*data*, *closed=None*, *dtype=None*, *copy=False*, *name=None*, *verify_integrity=True*)

Immutable index of intervals that are closed on the same side.

New in version 0.20.0.

Parameters

data [array-like (1-dimensional)] Array-like containing Interval objects from which to build the IntervalIndex.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

dtype [dtype or None, default None] If None, dtype will be inferred.

copy [bool, default False] Copy the input data.

name [object, optional] Name to be stored in the index.

verify_integrity [bool, default True] Verify that the IntervalIndex is valid.

See also:

Index The base pandas Index type.
Interval A bounded slice-like interval; the elements of an IntervalIndex.
interval_range Function to create a fixed frequency IntervalIndex.
cut Bin values into discrete Intervals.
qcut Bin values into equal-sized Intervals based on rank or sample quantiles.

Notes

See the user guide for more.

Examples

A new `IntervalIndex` is typically constructed using *interval_range()*:

```
>>> pd.interval_range(start=0, end=5)
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]],
              closed='right',
              dtype='interval[int64]')
```

It may also be constructed using one of the constructor methods: *IntervalIndex.from_arrays()*, *IntervalIndex.from_breaks()*, and *IntervalIndex.from_tuples()*.

See further examples in the doc strings of `interval_range` and the mentioned constructor methods.

Attributes

closed	Whether the intervals are closed on the left-side, right-side, both or neither.
length	Return the length of the Interval.
is_empty	Indicates if an interval is empty, meaning it contains no points.
is_non_overlapping_monotonic	Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.
is_overlapping	Return True if the IntervalIndex has overlapping intervals, else False.
values	Return the IntervalIndex's data as an IntervalArray.

pandas.IntervalIndex.closed

IntervalIndex.**closed**
Whether the intervals are closed on the left-side, right-side, both or neither.

pandas.IntervalIndex.length

property IntervalIndex.**length**
Return the length of the Interval.

pandas.IntervalIndex.is_empty

IntervalIndex.**is_empty**
Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

Returns

bool or ndarray A boolean indicating if a scalar *Interval* is empty, or a boolean ndarray positionally indicating if an Interval in an *IntervalArray* or *IntervalIndex* is empty.

Examples

An *Interval* that contains points is not empty:

```
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An Interval that does not contain any points is empty:

```
>>> pd.Interval(0, 0, closed='right').is_empty
True
>>> pd.Interval(0, 0, closed='left').is_empty
True
```

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```
>>> pd.Interval(0, 0, closed='neither').is_empty
True
```

An `Interval` that contains a single point is not empty:

```
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An *IntervalArray* or *IntervalIndex* returns a boolean `ndarray` positionally indicating if an `Interval` is empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'),
...        pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

pandas.IntervalIndex.is_non_overlapping_monotonic

IntervalIndex.**is_non_overlapping_monotonic**

Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

pandas.IntervalIndex.is_overlapping

property IntervalIndex.**is_overlapping**

Return True if the IntervalIndex has overlapping intervals, else False.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

Returns

bool Boolean indicating if the IntervalIndex has overlapping intervals.

See also:

Interval.overlaps Check whether two Interval objects overlap.

IntervalIndex.overlaps Check an IntervalIndex elementwise for overlaps.

Examples

```
>>> index = pd.IntervalIndex.from_tuples([(0, 2), (1, 3), (4, 5)])
>>> index
IntervalIndex([(0, 2], (1, 3], (4, 5]],
      closed='right',
      dtype='interval[int64]')
>>> index.is_overlapping
True
```

Intervals that share closed endpoints overlap:

```
>>> index = pd.interval_range(0, 3, closed='both')
>>> index
IntervalIndex([[0, 1], [1, 2], [2, 3]],
      closed='both',
      dtype='interval[int64]')
>>> index.is_overlapping
True
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> index = pd.interval_range(0, 3, closed='left')
>>> index
IntervalIndex([[0, 1), [1, 2), [2, 3)],
      closed='left',
      dtype='interval[int64]')
>>> index.is_overlapping
False
```

pandas.IntervalIndex.values

IntervalIndex.**values**

Return the IntervalIndex's data as an IntervalArray.

left	
right	
mid	

Methods

from_arrays(left, right[, closed, name, ...])	Construct from two arrays defining the left and right bounds.
from_tuples(data[, closed, name, copy, dtype])	Construct an IntervalIndex from an array-like of tuples.
from_breaks(breaks[, closed, name, copy, dtype])	Construct an IntervalIndex from an array of splits.
contains(*args, **kwargs)	Check elementwise if the Intervals contain the value.
overlaps(*args, **kwargs)	Check elementwise if an Interval overlaps the values in the IntervalArray.

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set_closed(*args, **kwargs)	Return an IntervalArray identical to the current one, but closed on the specified side.
to_tuples(*args, **kwargs)	Return an ndarray of tuples of the form (left, right).

pandas.IntervalIndex.from_arrays

classmethod IntervalIndex.**from_arrays**(*left*, *right*, *closed='right'*, *name=None*, *copy=False*, *dtype=None*)

Construct from two arrays defining the left and right bounds.

Parameters

left [array-like (1-dimensional)] Left bounds for each interval.

right [array-like (1-dimensional)] Right bounds for each interval.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

copy [bool, default False] Copy the data.

dtype [dtype, optional] If None, dtype will be inferred.

Returns

IntervalIndex

Raises

ValueError When a value is missing in only one of *left* or *right*. When a value in *left* is greater than the corresponding value in *right*.

See also:

interval_range Function to create a fixed frequency IntervalIndex.

IntervalIndex.from_breaks Construct an IntervalIndex from an array of splits.

IntervalIndex.from_tuples Construct an IntervalIndex from an array-like of tuples.

Notes

Each element of *left* must be less than or equal to the *right* element at the same position. If an element is missing, it must be missing in both *left* and *right*. A TypeError is raised when using an unsupported type for *left* or *right*. At the moment, 'category', 'object', and 'string' subtypes are not supported.

Examples

```
>>> pd.IntervalIndex.from_arrays([0, 1, 2], [1, 2, 3])
IntervalIndex([(0, 1], (1, 2], (2, 3]],
              closed='right',
              dtype='interval[int64]')
```

pandas.IntervalIndex.from_tuples

classmethod IntervalIndex.**from_tuples**(*data*, *closed='right'*, *name=None*, *copy=False*, *dtype=None*)

Construct an IntervalIndex from an array-like of tuples.

Parameters

data [array-like (1-dimensional)] Array of tuples.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

copy [bool, default False] By-default copy the data, this is compat only and ignored.

dtype [dtype or None, default None] If None, dtype will be inferred.

Returns

IntervalIndex

See also:

interval_range Function to create a fixed frequency IntervalIndex.

IntervalIndex.from_arrays Construct an IntervalIndex from a left and right array.

IntervalIndex.from_breaks Construct an IntervalIndex from an array of splits.

Examples

```
>>> pd.IntervalIndex.from_tuples([(0, 1), (1, 2)])
IntervalIndex([(0, 1], (1, 2]],
              closed='right',
              dtype='interval[int64]')
```

pandas.IntervalIndex.from_breaks

classmethod IntervalIndex.**from_breaks**(*breaks*, *closed='right'*, *name=None*, *copy=False*, *dtype=None*)

Construct an IntervalIndex from an array of splits.

Parameters

breaks [array-like (1-dimensional)] Left and right bounds for each interval.

closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.

copy [bool, default False] Copy the data.

dtype [dtype or None, default None] If None, dtype will be inferred.

Returns

IntervalIndex

See also:

interval_range Function to create a fixed frequency IntervalIndex.

IntervalIndex.from_arrays Construct from a left and right array.

IntervalIndex.from_tuples Construct from a sequence of tuples.

Examples

```
>>> pd.IntervalIndex.from_breaks([0, 1, 2, 3])
IntervalIndex([(0, 1], (1, 2], (2, 3]],
              closed='right',
              dtype='interval[int64]')
```

pandas.IntervalIndex.contains

IntervalIndex.**contains**(**args*, ***kwargs*)

Check elementwise if the Intervals contain the value.

Return a boolean mask whether the value is contained in the Intervals of the IntervalArray.

New in version 0.25.0.

Parameters

other [scalar] The value to check whether it is contained in the Intervals.

Returns

boolean array

See also:

Interval.contains Check whether Interval object contains value.

IntervalArray.overlaps Check if an Interval overlaps the values in the IntervalArray.

Examples

```
>>> intervals = pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 3), (2, 4)])
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.contains(0.5)
array([ True, False, False])
```

pandas.IntervalIndex.overlaps

IntervalIndex.**overlaps**(**args*, ***kwargs*)

Check elementwise if an Interval overlaps the values in the IntervalArray.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

Parameters

other [IntervalArray] Interval to check against for an overlap.

Returns

ndarray Boolean array positionally indicating where an overlap occurs.

See also:

Interval.overlaps Check whether two Interval objects overlap.

Examples

```
>>> data = [(0, 1), (1, 3), (2, 4)]
>>> intervals = pd.arrays.IntervalArray.from_tuples(data)
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.overlaps(pd.Interval(0.5, 1.5))
array([ True,  True, False])
```

Intervals that share closed endpoints overlap:

```
>>> intervals.overlaps(pd.Interval(1, 3, closed='left'))
array([ True,  True, True])
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> intervals.overlaps(pd.Interval(1, 2, closed='right'))
array([False,  True, False])
```

pandas.IntervalIndex.set_closed

IntervalIndex.**set_closed**(**args*, ***kwargs*)

Return an IntervalArray identical to the current one, but closed on the specified side.

New in version 0.24.0.

Parameters

closed [{'left', 'right', 'both', 'neither'}] Whether the intervals are closed on the left-side, right-side, both or neither.

Returns

new_index [IntervalArray]

Examples

```
>>> index = pd.arrays.IntervalArray.from_breaks(range(4))
>>> index
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
>>> index.set_closed('both')
<IntervalArray>
[[0, 1], [1, 2], [2, 3]]
Length: 3, closed: both, dtype: interval[int64]
```

pandas.IntervalIndex.to_tuples

IntervalIndex.**to_tuples**(**args*, ***kwargs*)

Return an ndarray of tuples of the form (left, right).

Parameters

na_tuple [bool, default True] Returns NA as a tuple if True, `(nan, nan)`, or just as the NA value itself if False, `nan`.

Returns

tuples: ndarray

IntervalIndex components

IntervalIndex.from_arrays(left, right[, ...])	Construct from two arrays defining the left and right bounds.
IntervalIndex.from_tuples(data[, closed, ...])	Construct an IntervalIndex from an array-like of tuples.
IntervalIndex.from_breaks(breaks[, closed, ...])	Construct an IntervalIndex from an array of splits.
IntervalIndex.left	
IntervalIndex.right	
IntervalIndex.mid	
IntervalIndex.closed	Whether the intervals are closed on the left-side, right-side, both or neither.
IntervalIndex.length	Return the length of the Interval.
IntervalIndex.values	Return the IntervalIndex's data as an IntervalArray.
IntervalIndex.is_empty	Indicates if an interval is empty, meaning it contains no points.
IntervalIndex.is_non_overlapping_monotonic	Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.
IntervalIndex.is_overlapping	Return True if the IntervalIndex has overlapping intervals, else False.

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IntervalIndex.get_loc(key[, method, tolerance])	Get integer location, slice or boolean mask for requested label.
IntervalIndex.get_indexer(target[, method, ...])	Compute indexer and mask for new index given the current index.
IntervalIndex.set_closed(*args, **kwargs)	Return an IntervalArray identical to the current one, but closed on the specified side.
IntervalIndex.contains(*args, **kwargs)	Check elementwise if the Intervals contain the value.
IntervalIndex.overlaps(*args, **kwargs)	Check elementwise if an Interval overlaps the values in the IntervalArray.
IntervalIndex.to_tuples(*args, **kwargs)	Return an ndarray of tuples of the form (left, right).

pandas.IntervalIndex.left

IntervalIndex.**left**

pandas.IntervalIndex.right

IntervalIndex.**right**

pandas.IntervalIndex.mid

IntervalIndex.**mid**

pandas.IntervalIndex.get_loc

IntervalIndex.**get_loc**(*key*, *method=None*, *tolerance=None*)

Get integer location, slice or boolean mask for requested label.

Parameters

key [label]

method [{None}, optional]

- default: matches where the label is within an interval only.

Returns

int if unique index, slice if monotonic index, else mask

Examples

```
>>> i1, i2 = pd.Interval(0, 1), pd.Interval(1, 2)
>>> index = pd.IntervalIndex([i1, i2])
>>> index.get_loc(1)
0
```

You can also supply a point inside an interval.

```
>>> index.get_loc(1.5)
1
```

If a label is in several intervals, you get the locations of all the relevant intervals.

```
>>> i3 = pd.Interval(0, 2)
>>> overlapping_index = pd.IntervalIndex([i1, i2, i3])
>>> overlapping_index.get_loc(0.5)
array([ True, False,  True])
```

Only exact matches will be returned if an interval is provided.

```
>>> index.get_loc(pd.Interval(0, 1))
0
```

pandas.IntervalIndex.get_indexer

IntervalIndex.**get_indexer**(*target*, *method=None*, *limit=None*, *tolerance=None*)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

Parameters

target [IntervalIndex or list of Intervals]

method [{None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}, optional]

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit [int, optional] Maximum number of consecutive labels in `target` to match for inexact matches.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

Returns

indexer [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Raises

NotImplementedError If any method argument other than the default of None is specified as these are not yet implemented.

Examples

```
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1,  2, -1])
```

Notice that the return value is an array of locations in `index` and `x` is marked by -1, as it is not in `index`.

3.6.5 MultiIndex

MultiIndex([levels, codes, sortorder, ...])	A multi-level, or hierarchical, index object for pandas objects.

pandas.MultiIndex

class pandas.**MultiIndex**(*levels=None*, *codes=None*, *sortorder=None*, *names=None*, *dtype=None*, *copy=False*, *name=None*, *verify_integrity=True*)

A multi-level, or hierarchical, index object for pandas objects.

Parameters

levels [sequence of arrays] The unique labels for each level.

codes [sequence of arrays] Integers for each level designating which label at each location.

New in version 0.24.0.

sortorder [optional int] Level of sortedness (must be lexicographically sorted by that level).

names [optional sequence of objects] Names for each of the index levels. (name is accepted for compat).

copy [bool, default False] Copy the meta-data.

verify_integrity [bool, default True] Check that the levels/codes are consistent and valid.

See also:

MultiIndex.from_arrays Convert list of arrays to MultiIndex.
MultiIndex.from_product Create a MultiIndex from the cartesian product of iterables.
MultiIndex.from_tuples Convert list of tuples to a MultiIndex.
MultiIndex.from_frame Make a MultiIndex from a DataFrame.
Index The base pandas Index type.

Notes

See the user guide for more.

Examples

A new `MultiIndex` is typically constructed using one of the helper methods *`MultiIndex.from_arrays()`*, *`MultiIndex.from_product()`* and *`MultiIndex.from_tuples()`*. For example (using `.from_arrays`):

```
>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> pd.MultiIndex.from_arrays(arrays, names=('number', 'color'))
MultiIndex([(1,  'red'),
            (1, 'blue'),
            (2,  'red'),
            (2, 'blue')],
           names=['number', 'color'])
```

See further examples for how to construct a MultiIndex in the doc strings of the mentioned helper methods.

Attributes

`names`	Names of levels in MultiIndex.
`nlevels`	Integer number of levels in this MultiIndex.
`levshape`	A tuple with the length of each level.

pandas.MultiIndex.names

property MultiIndex.**names**

Names of levels in MultiIndex.

Examples

```
>>> mi = pd.MultiIndex.from_arrays(
... [[1, 2], [3, 4], [5, 6]], names=['x', 'y', 'z'])
>>> mi
MultiIndex([(1, 3, 5),
            (2, 4, 6)],
           names=['x', 'y', 'z'])
>>> mi.names
FrozenList(['x', 'y', 'z'])
```

pandas.MultiIndex.nlevels

property MultiIndex.**nlevels**

Integer number of levels in this MultiIndex.

Examples

```
>>> mi = pd.MultiIndex.from_arrays([['a'], ['b'], ['c']])
>>> mi
MultiIndex([('a', 'b', 'c')],
           )
>>> mi.nlevels
3
```

pandas.MultiIndex.levshape

property MultiIndex.**levshape**

A tuple with the length of each level.

Examples

```
>>> mi = pd.MultiIndex.from_arrays([['a'], ['b'], ['c']])
>>> mi
MultiIndex([('a', 'b', 'c')],
           )
>>> mi.levshape
(1, 1, 1)
```

levels	
codes	

Methods

from_arrays(arrays[, sortorder, names])	Convert arrays to MultiIndex.
from_tuples(tuples[, sortorder, names])	Convert list of tuples to MultiIndex.
from_product(iterables[, sortorder, names])	Make a MultiIndex from the cartesian product of multiple iterables.
from_frame(df[, sortorder, names])	Make a MultiIndex from a DataFrame.
set_levels(levels[, level, inplace, ...])	Set new levels on MultiIndex.
set_codes(codes[, level, inplace, ...])	Set new codes on MultiIndex.
to_frame([index, name])	Create a DataFrame with the levels of the MultiIndex as columns.
to_flat_index()	Convert a MultiIndex to an Index of Tuples containing the level values.
is_lexsorted()	Return True if the codes are lexicographically sorted.
sortlevel([level, ascending, sort_remaining])	Sort MultiIndex at the requested level.
droplevel([level])	Return index with requested level(s) removed.
swaplevel([i, j])	Swap level i with level j.
reorder_levels(order)	Rearrange levels using input order.
remove_unused_levels()	Create new MultiIndex from current that removes unused levels.
get_locs(seq)	Get location for a sequence of labels.

pandas.MultiIndex.from_arrays

classmethod MultiIndex.**from_arrays**(*arrays*, *sortorder=None*, *names=<object object>*)

Convert arrays to MultiIndex.

Parameters

arrays [list / sequence of array-likes] Each array-like gives one level's value for each data point. len(arrays) is the number of levels.

sortorder [int or None] Level of sortedness (must be lexicographically sorted by that level).

names [list / sequence of str, optional] Names for the levels in the index.

Returns

MultiIndex

See also:

MultiIndex.from_tuples Convert list of tuples to MultiIndex.

MultiIndex.from_product Make a MultiIndex from cartesian product of iterables.

MultiIndex.from_frame Make a MultiIndex from a DataFrame.

Examples

```
>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> pd.MultiIndex.from_arrays(arrays, names=('number', 'color'))
MultiIndex([(1,  'red'),
            (1, 'blue'),
            (2,  'red'),
            (2, 'blue')],
           names=['number', 'color'])
```

pandas.MultiIndex.from_tuples

classmethod MultiIndex.**from_tuples**(*tuples*, *sortorder=None*, *names=None*)

Convert list of tuples to MultiIndex.

Parameters

tuples [list / sequence of tuple-likes] Each tuple is the index of one row/column.

sortorder [int or None] Level of sortedness (must be lexicographically sorted by that level).

names [list / sequence of str, optional] Names for the levels in the index.

Returns

MultiIndex

See also:

MultiIndex.from_arrays Convert list of arrays to MultiIndex.

MultiIndex.from_product Make a MultiIndex from cartesian product of iterables.

MultiIndex.from_frame Make a MultiIndex from a DataFrame.

Examples

```
>>> tuples = [(1, 'red'), (1, 'blue'),
...           (2, 'red'), (2, 'blue')]
>>> pd.MultiIndex.from_tuples(tuples, names=('number', 'color'))
MultiIndex([(1,  'red'),
            (1, 'blue'),
            (2,  'red'),
            (2, 'blue')],
           names=['number', 'color'])
```

pandas.MultiIndex.from_product

classmethod MultiIndex.**from_product**(*iterables*, *sortorder=None*, *names=<object object>*)

Make a MultiIndex from the cartesian product of multiple iterables.

Parameters

iterables [list / sequence of iterables] Each iterable has unique labels for each level of the index.

sortorder [int or None] Level of sortedness (must be lexicographically sorted by that level).

names [list / sequence of str, optional] Names for the levels in the index.

Changed in version 1.0.0: If not explicitly provided, names will be inferred from the elements of iterables if an element has a name attribute

Returns

MultiIndex

See also:

MultiIndex.from_arrays Convert list of arrays to MultiIndex.

MultiIndex.from_tuples Convert list of tuples to MultiIndex.

MultiIndex.from_frame Make a MultiIndex from a DataFrame.

Examples

```
>>> numbers = [0, 1, 2]
>>> colors = ['green', 'purple']
>>> pd.MultiIndex.from_product([numbers, colors],
...                            names=['number', 'color'])
MultiIndex([(0,  'green'),
            (0, 'purple'),
            (1,  'green'),
            (1, 'purple'),
            (2,  'green'),
            (2, 'purple')],
           names=['number', 'color'])
```

pandas.MultiIndex.from_frame

classmethod MultiIndex.**from_frame**(*df*, *sortorder=None*, *names=None*)

Make a MultiIndex from a DataFrame.

New in version 0.24.0.

Parameters

df [DataFrame] DataFrame to be converted to MultiIndex.

sortorder [int, optional] Level of sortedness (must be lexicographically sorted by that level).

names [list-like, optional] If no names are provided, use the column names, or tuple of column names if the columns is a MultiIndex. If a sequence, overwrite names with the given sequence.

Returns

MultiIndex The MultiIndex representation of the given DataFrame.

See also:

MultiIndex.from_arrays Convert list of arrays to MultiIndex.

MultiIndex.from_tuples Convert list of tuples to MultiIndex.

MultiIndex.from_product Make a MultiIndex from cartesian product of iterables.

Examples

```
>>> df = pd.DataFrame([['HI', 'Temp'], ['HI', 'Precip'],
...                    ['NJ', 'Temp'], ['NJ', 'Precip']],
...                   columns=['a', 'b'])
>>> df
      a       b
0    HI    Temp
1    HI  Precip
2    NJ    Temp
3    NJ  Precip
```

```
>>> pd.MultiIndex.from_frame(df)
MultiIndex([('HI',   'Temp'),
            ('HI', 'Precip'),
            ('NJ',   'Temp'),
            ('NJ', 'Precip')],
           names=['a', 'b'])
```

Using explicit names, instead of the column names

```
>>> pd.MultiIndex.from_frame(df, names=['state', 'observation'])
MultiIndex([('HI',   'Temp'),
            ('HI', 'Precip'),
            ('NJ',   'Temp'),
            ('NJ', 'Precip')],
           names=['state', 'observation'])
```

pandas.MultiIndex.set_levels

MultiIndex.**set_levels**(*levels*, *level=None*, *inplace=None*, *verify_integrity=True*)

Set new levels on MultiIndex. Defaults to returning new index.

Parameters

levels [sequence or list of sequence] New level(s) to apply.

level [int, level name, or sequence of int/level names (default None)] Level(s) to set (None for all levels).

inplace [bool] If True, mutates in place.

Deprecated since version 1.2.0.

verify_integrity [bool, default True] If True, checks that levels and codes are compatible.

Returns

new index (of same type and class...etc) or None The same type as the caller or None if `inplace=True`.

Examples

```
>>> idx = pd.MultiIndex.from_tuples(
...     [
...         (1, "one"),
...         (1, "two"),
...         (2, "one"),
...         (2, "two"),
...         (3, "one"),
...         (3, "two")
...     ],
...     names=["foo", "bar"]
... )
>>> idx
MultiIndex([(1, 'one'),
    (1, 'two'),
    (2, 'one'),
    (2, 'two'),
    (3, 'one'),
    (3, 'two')],
   names=['foo', 'bar'])
```

```
>>> idx.set_levels([['a', 'b', 'c'], [1, 2]])
MultiIndex([('a', 1),
            ('a', 2),
            ('b', 1),
            ('b', 2),
            ('c', 1),
            ('c', 2)],
           names=['foo', 'bar'])
>>> idx.set_levels(['a', 'b', 'c'], level=0)
MultiIndex([('a', 'one'),
            ('a', 'two'),
            ('b', 'one'),
```

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```
            ('b', 'two'),
            ('c', 'one'),
            ('c', 'two')],
           names=['foo', 'bar'])
>>> idx.set_levels(['a', 'b'], level='bar')
MultiIndex([(1, 'a'),
            (1, 'b'),
            (2, 'a'),
            (2, 'b'),
            (3, 'a'),
            (3, 'b')],
           names=['foo', 'bar'])
```

If any of the levels passed to `set_levels()` exceeds the existing length, all of the values from that argument will be stored in the MultiIndex levels, though the values will be truncated in the MultiIndex output.

```
>>> idx.set_levels([['a', 'b', 'c'], [1, 2, 3, 4]], level=[0, 1])
MultiIndex([('a', 1),
    ('a', 2),
    ('b', 1),
    ('b', 2),
    ('c', 1),
    ('c', 2)],
   names=['foo', 'bar'])
>>> idx.set_levels([['a', 'b', 'c'], [1, 2, 3, 4]], level=[0, 1]).levels
FrozenList([['a', 'b', 'c'], [1, 2, 3, 4]])
```

pandas.MultiIndex.set_codes

`MultiIndex.set_codes`(*codes*, *level=None*, *inplace=None*, *verify_integrity=True*)

Set new codes on MultiIndex. Defaults to returning new index.

New in version 0.24.0: New name for deprecated method *set_labels*.

Parameters

codes [sequence or list of sequence] New codes to apply.

level [int, level name, or sequence of int/level names (default None)] Level(s) to set (None for all levels).

inplace [bool] If True, mutates in place.

Deprecated since version 1.2.0.

verify_integrity [bool (default True)] If True, checks that levels and codes are compatible.

Returns

new index (of same type and class...etc) or None The same type as the caller or None if `inplace=True`.

Examples

```
>>> idx = pd.MultiIndex.from_tuples(
...     [(1, "one"), (1, "two"), (2, "one"), (2, "two")], names=["foo", "bar
↪"]
... )
>>> idx
MultiIndex([(1, 'one'),
    (1, 'two'),
    (2, 'one'),
    (2, 'two')],
   names=['foo', 'bar'])
```

```
>>> idx.set_codes([[1, 0, 1, 0], [0, 0, 1, 1]])
MultiIndex([(2, 'one'),
            (1, 'one'),
            (2, 'two'),
            (1, 'two')],
           names=['foo', 'bar'])
>>> idx.set_codes([1, 0, 1, 0], level=0)
MultiIndex([(2, 'one'),
            (1, 'two'),
            (2, 'one'),
            (1, 'two')],
           names=['foo', 'bar'])
>>> idx.set_codes([0, 0, 1, 1], level='bar')
MultiIndex([(1, 'one'),
            (1, 'one'),
            (2, 'two'),
            (2, 'two')],
           names=['foo', 'bar'])
>>> idx.set_codes([[1, 0, 1, 0], [0, 0, 1, 1]], level=[0, 1])
MultiIndex([(2, 'one'),
            (1, 'one'),
            (2, 'two'),
            (1, 'two')],
           names=['foo', 'bar'])
```

pandas.MultiIndex.to_frame

MultiIndex.**to_frame**(*index=True*, *name=None*)

Create a DataFrame with the levels of the MultiIndex as columns.

Column ordering is determined by the DataFrame constructor with data as a dict.

New in version 0.24.0.

Parameters

index [bool, default True] Set the index of the returned DataFrame as the original MultiIndex.

name [list / sequence of str, optional] The passed names should substitute index level names.

Returns

DataFrame [a DataFrame containing the original MultiIndex data.]

See also:

DataFrame Two-dimensional, size-mutable, potentially heterogeneous tabular data.

Examples

```
>>> mi = pd.MultiIndex.from_arrays([['a', 'b'], ['c', 'd']])
>>> mi
MultiIndex([('a', 'c'),
            ('b', 'd')],
           )
```

```
>>> df = mi.to_frame()
>>> df
     0  1
a c  a  c
b d  b  d
```

```
>>> df = mi.to_frame(index=False)
>>> df
   0  1
0  a  c
1  b  d
```

```
>>> df = mi.to_frame(name=['x', 'y'])
>>> df
     x  y
a c  a  c
b d  b  d
```

pandas.MultiIndex.to_flat_index

MultiIndex.**to_flat_index**()

Convert a MultiIndex to an Index of Tuples containing the level values.

New in version 0.24.0.

Returns

pd.Index Index with the MultiIndex data represented in Tuples.

Notes

This method will simply return the caller if called by anything other than a MultiIndex.

Examples

```
>>> index = pd.MultiIndex.from_product(
...     [['foo', 'bar'], ['baz', 'qux']],
...     names=['a', 'b'])
>>> index.to_flat_index()
Index([('foo', 'baz'), ('foo', 'qux'),
       ('bar', 'baz'), ('bar', 'qux')],
      dtype='object')
```

pandas.MultiIndex.is_lexsorted

MultiIndex.**is_lexsorted**()

Return True if the codes are lexicographically sorted.

Returns

bool

Examples

In the below examples, the first level of the MultiIndex is sorted because a<b<c, so there is no need to look at the next level.

```
>>> pd.MultiIndex.from_arrays([['a', 'b', 'c'], ['d', 'e', 'f']]).is_
↪lexsorted()
True
>>> pd.MultiIndex.from_arrays([['a', 'b', 'c'], ['d', 'f', 'e']]).is_
↪lexsorted()
True
```

In case there is a tie, the lexicographical sorting looks at the next level of the MultiIndex.

```
>>> pd.MultiIndex.from_arrays([[0, 1, 1], ['a', 'b', 'c']]).is_lexsorted()
True
>>> pd.MultiIndex.from_arrays([[0, 1, 1], ['a', 'c', 'b']]).is_lexsorted()
False
>>> pd.MultiIndex.from_arrays([['a', 'a', 'b', 'b'],
...                            ['aa', 'bb', 'aa', 'bb']]).is_lexsorted()
True
>>> pd.MultiIndex.from_arrays([['a', 'a', 'b', 'b'],
...                            ['bb', 'aa', 'aa', 'bb']]).is_lexsorted()
False
```

pandas.MultiIndex.sortlevel

MultiIndex.**sortlevel**(*level=0*, *ascending=True*, *sort_remaining=True*)

Sort MultiIndex at the requested level.

The result will respect the original ordering of the associated factor at that level.

Parameters

level [list-like, int or str, default 0] If a string is given, must be a name of the level. If list-like must be names or ints of levels.

ascending [bool, default True] False to sort in descending order. Can also be a list to specify a directed ordering.

sort_remaining [sort by the remaining levels after level]

Returns

sorted_index [pd.MultiIndex] Resulting index.

indexer [np.ndarray] Indices of output values in original index.

Examples

```
>>> mi = pd.MultiIndex.from_arrays([[0, 0], [2, 1]])
>>> mi
MultiIndex([(0, 2),
            (0, 1)],
           )
```

```
>>> mi.sortlevel()
(MultiIndex([(0, 1),
             (0, 2)],
            ), array([1, 0]))
```

```
>>> mi.sortlevel(sort_remaining=False)
(MultiIndex([(0, 2),
             (0, 1)],
            ), array([0, 1]))
```

```
>>> mi.sortlevel(1)
(MultiIndex([(0, 1),
             (0, 2)],
            ), array([1, 0]))
```

```
>>> mi.sortlevel(1, ascending=False)
(MultiIndex([(0, 2),
             (0, 1)],
            ), array([0, 1]))
```

pandas.MultiIndex.droplevel

MultiIndex.**droplevel**(*level=0*)

Return index with requested level(s) removed.

If resulting index has only 1 level left, the result will be of Index type, not MultiIndex.

Parameters

level [int, str, or list-like, default 0] If a string is given, must be the name of a level If list-like, elements must be names or indexes of levels.

Returns

Index or MultiIndex

Examples

```
>>> mi = pd.MultiIndex.from_arrays(
... [[1, 2], [3, 4], [5, 6]], names=['x', 'y', 'z'])
>>> mi
MultiIndex([(1, 3, 5),
            (2, 4, 6)],
           names=['x', 'y', 'z'])
```

```
>>> mi.droplevel()
MultiIndex([(3, 5),
            (4, 6)],
           names=['y', 'z'])
```

```
>>> mi.droplevel(2)
MultiIndex([(1, 3),
            (2, 4)],
           names=['x', 'y'])
```

```
>>> mi.droplevel('z')
MultiIndex([(1, 3),
            (2, 4)],
           names=['x', 'y'])
```

```
>>> mi.droplevel(['x', 'y'])
Int64Index([5, 6], dtype='int64', name='z')
```

pandas.MultiIndex.swaplevel

MultiIndex.**swaplevel**(*i=-2*, *j=-1*)

Swap level i with level j.

Calling this method does not change the ordering of the values.

Parameters

i [int, str, default -2] First level of index to be swapped. Can pass level name as string. Type of parameters can be mixed.

j [int, str, default -1] Second level of index to be swapped. Can pass level name as string. Type of parameters can be mixed.

Returns

MultiIndex A new MultiIndex.

See also:

Series.swaplevel Swap levels i and j in a MultiIndex.

Dataframe.swaplevel Swap levels i and j in a MultiIndex on a particular axis.

Examples

```
>>> mi = pd.MultiIndex(levels=[['a', 'b'], ['bb', 'aa']],
...                    codes=[[0, 0, 1, 1], [0, 1, 0, 1]])
>>> mi
MultiIndex([('a', 'bb'),
            ('a', 'aa'),
            ('b', 'bb'),
            ('b', 'aa')],
           )
>>> mi.swaplevel(0, 1)
MultiIndex([('bb', 'a'),
            ('aa', 'a'),
            ('bb', 'b'),
            ('aa', 'b')],
           )
```

pandas.MultiIndex.reorder_levels

MultiIndex.**reorder_levels**(*order*)

Rearrange levels using input order. May not drop or duplicate levels.

Parameters

order [list of int or list of str] List representing new level order. Reference level by number (position) or by key (label).

Returns

MultiIndex

Examples

```
>>> mi = pd.MultiIndex.from_arrays([[1, 2], [3, 4]], names=['x', 'y'])
>>> mi
MultiIndex([(1, 3),
            (2, 4)],
           names=['x', 'y'])
```

```
>>> mi.reorder_levels(order=[1, 0])
MultiIndex([(3, 1),
            (4, 2)],
           names=['y', 'x'])
```

```
>>> mi.reorder_levels(order=['y', 'x'])
MultiIndex([(3, 1),
            (4, 2)],
           names=['y', 'x'])
```

pandas.MultiIndex.remove_unused_levels

MultiIndex.**remove_unused_levels**()

Create new MultiIndex from current that removes unused levels.

Unused level(s) means levels that are not expressed in the labels. The resulting MultiIndex will have the same outward appearance, meaning the same .values and ordering. It will also be .equals() to the original.

Returns

MultiIndex

Examples

```
>>> mi = pd.MultiIndex.from_product([range(2), list('ab')])
>>> mi
MultiIndex([(0, 'a'),
            (0, 'b'),
            (1, 'a'),
            (1, 'b')],
           )
```

```
>>> mi[2:]
MultiIndex([(1, 'a'),
            (1, 'b')],
           )
```

The 0 from the first level is not represented and can be removed

```
>>> mi2 = mi[2:].remove_unused_levels()
>>> mi2.levels
FrozenList([[1], ['a', 'b']])
```

pandas.MultiIndex.get_locs

MultiIndex.**get_locs**(*seq*)

Get location for a sequence of labels.

Parameters

seq [label, slice, list, mask or a sequence of such] You should use one of the above for each level. If a level should not be used, set it to `slice(None)`.

Returns

numpy.ndarray NumPy array of integers suitable for passing to iloc.

See also:

MultiIndex.get_loc Get location for a label or a tuple of labels.

MultiIndex.slice_locs Get slice location given start label(s) and end label(s).

Examples

```
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')])
```

```
>>> mi.get_locs('b')
array([1, 2], dtype=int64)
```

```
>>> mi.get_locs([slice(None), ['e', 'f']])
array([1, 2], dtype=int64)
```

```
>>> mi.get_locs([[True, False, True], slice('e', 'f')])
array([2], dtype=int64)
```

IndexSlice	Create an object to more easily perform multi-index slicing.

pandas.IndexSlice

pandas.**IndexSlice = <pandas.core.indexing._IndexSlice object>**

Create an object to more easily perform multi-index slicing.

See also:

MultiIndex.remove_unused_levels New MultiIndex with no unused levels.

Notes

See *Defined Levels* for further info on slicing a MultiIndex.

Examples

```
>>> midx = pd.MultiIndex.from_product([['A0','A1'], ['B0','B1','B2','B3']])
>>> columns = ['foo', 'bar']
>>> dfmi = pd.DataFrame(np.arange(16).reshape((len(midx), len(columns))),
...                     index=midx, columns=columns)
```

Using the default slice command:

```
>>> dfmi.loc[(slice(None), slice('B0', 'B1')), :]
           foo  bar
    A0 B0    0    1
       B1    2    3
    A1 B0    8    9
       B1   10   11
```

Using the IndexSlice class for a more intuitive command:

```
>>> idx = pd.IndexSlice
>>> dfmi.loc[idx[:, 'B0':'B1'], :]
           foo  bar
    A0 B0    0    1
       B1    2    3
```

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```
    A1 B0    8    9
       B1   10   11
```

MultiIndex constructors

`MultiIndex.from_arrays`(arrays[, sortorder, ...])	Convert arrays to MultiIndex.
`MultiIndex.from_tuples`(tuples[, sortorder, ...])	Convert list of tuples to MultiIndex.
`MultiIndex.from_product`(iterables[, ...])	Make a MultiIndex from the cartesian product of multiple iterables.
`MultiIndex.from_frame`(df[, sortorder, names])	Make a MultiIndex from a DataFrame.

MultiIndex properties

`MultiIndex.names`	Names of levels in MultiIndex.
`MultiIndex.levels`	
`MultiIndex.codes`	
`MultiIndex.nlevels`	Integer number of levels in this MultiIndex.
`MultiIndex.levshape`	A tuple with the length of each level.

pandas.MultiIndex.levels

MultiIndex.**levels**

pandas.MultiIndex.codes

property MultiIndex.**codes**

MultiIndex components

`MultiIndex.set_levels`(levels[, level, ...])	Set new levels on MultiIndex.
`MultiIndex.set_codes`(codes[, level, ...])	Set new codes on MultiIndex.
`MultiIndex.to_flat_index`()	Convert a MultiIndex to an Index of Tuples containing the level values.
`MultiIndex.to_frame`([index, name])	Create a DataFrame with the levels of the MultiIndex as columns.
`MultiIndex.is_lexsorted`()	Return True if the codes are lexicographically sorted.
`MultiIndex.sortlevel`([level, ascending, ...])	Sort MultiIndex at the requested level.
`MultiIndex.droplevel`([level])	Return index with requested level(s) removed.
`MultiIndex.swaplevel`([i, j])	Swap level i with level j.
`MultiIndex.reorder_levels`(order)	Rearrange levels using input order.
`MultiIndex.remove_unused_levels`()	Create new MultiIndex from current that removes unused levels.

MultiIndex selecting

MultiIndex.get_loc(key[, method])	Get location for a label or a tuple of labels.
MultiIndex.get_locs(seq)	Get location for a sequence of labels.
MultiIndex.get_loc_level(key[, level, ...])	Get location and sliced index for requested label(s)/level(s).
MultiIndex.get_indexer(target[, method, ...])	Compute indexer and mask for new index given the current index.
MultiIndex.get_level_values(level)	Return vector of label values for requested level.

pandas.MultiIndex.get_loc

MultiIndex.**get_loc**(*key*, *method=None*)

Get location for a label or a tuple of labels.

The location is returned as an integer/slice or boolean mask.

Parameters

key [label or tuple of labels (one for each level)]

method [None]

Returns

loc [int, slice object or boolean mask] If the key is past the lexsort depth, the return may be a boolean mask array, otherwise it is always a slice or int.

See also:

Index.get_loc The get_loc method for (single-level) index.
MultiIndex.slice_locs Get slice location given start label(s) and end label(s).
MultiIndex.get_locs Get location for a label/slice/list/mask or a sequence of such.

Notes

The key cannot be a slice, list of same-level labels, a boolean mask, or a sequence of such. If you want to use those, use *MultiIndex.get_locs()* instead.

Examples

```
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')])
```

```
>>> mi.get_loc('b')
slice(1, 3, None)
```

```
>>> mi.get_loc(('b', 'e'))
1
```

pandas.MultiIndex.get_loc_level

MultiIndex.**get_loc_level**(*key*, *level=0*, *drop_level=True*)

Get location and sliced index for requested label(s)/level(s).

Parameters

key [label or sequence of labels]

level [int/level name or list thereof, optional]

drop_level [bool, default True] If `False`, the resulting index will not drop any level.

Returns

loc [A 2-tuple where the elements are:] Element 0: int, slice object or boolean array Element 1: The resulting sliced multiindex/index. If the key contains all levels, this will be `None`.

See also:

MultiIndex.get_loc Get location for a label or a tuple of labels.
MultiIndex.get_locs Get location for a label/slice/list/mask or a sequence of such.

Examples

```
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')],
...                                names=['A', 'B'])
```

```
>>> mi.get_loc_level('b')
(slice(1, 3, None), Index(['e', 'f'], dtype='object', name='B'))
```

```
>>> mi.get_loc_level('e', level='B')
(array([False,  True, False]), Index(['b'], dtype='object', name='A'))
```

```
>>> mi.get_loc_level(['b', 'e'])
(1, None)
```

pandas.MultiIndex.get_indexer

MultiIndex.**get_indexer**(*target*, *method=None*, *limit=None*, *tolerance=None*)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

Parameters

target [MultiIndex or list of tuples]

method [{None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}, optional]

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit [int, optional] Maximum number of consecutive labels in `target` to match for inexact matches.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

Returns

indexer [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1,  2, -1])
```

Notice that the return value is an array of locations in `index` and `x` is marked by -1, as it is not in `index`.

pandas.MultiIndex.get_level_values

`MultiIndex.`**`get_level_values`**(*level*)

Return vector of label values for requested level.

Length of returned vector is equal to the length of the index.

Parameters

level [int or str] `level` is either the integer position of the level in the MultiIndex, or the name of the level.

Returns

values [Index] Values is a level of this MultiIndex converted to a single *Index* (or subclass thereof).

Examples

Create a MultiIndex:

```
>>> mi = pd.MultiIndex.from_arrays((list('abc'), list('def')))
>>> mi.names = ['level_1', 'level_2']
```

Get level values by supplying level as either integer or name:

```
>>> mi.get_level_values(0)
Index(['a', 'b', 'c'], dtype='object', name='level_1')
>>> mi.get_level_values('level_2')
Index(['d', 'e', 'f'], dtype='object', name='level_2')
```

3.6.6 DatetimeIndex

`DatetimeIndex`([data, freq, tz, normalize, ...])	Immutable ndarray-like of datetime64 data.

pandas.DatetimeIndex

class pandas.**DatetimeIndex**(*data=None*, *freq=<object object>*, *tz=None*, *normalize=False*, *closed=None*, *ambiguous='raise'*, *dayfirst=False*, *yearfirst=False*, *dtype=None*, *copy=False*, *name=None*)

Immutable ndarray-like of datetime64 data.

Represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata.

Parameters

data [array-like (1-dimensional), optional] Optional datetime-like data to construct index with.

freq [str or pandas offset object, optional] One of pandas date offset strings or corresponding objects. The string 'infer' can be passed in order to set the frequency of the index as the inferred frequency upon creation.

tz [pytz.timezone or dateutil.tz.tzfile or datetime.tzinfo or str] Set the Timezone of the data.

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

closed [{'left', 'right'}, optional] Set whether to include *start* and *end* that are on the boundary. The default includes boundary points on either end.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

dayfirst [bool, default False] If True, parse dates in *data* with the day first order.

yearfirst [bool, default False] If True parse dates in *data* with the year first order.

dtype [numpy.dtype or DatetimeTZDtype or str, default None] Note that the only NumPy dtype allowed is 'datetime64[ns]'.

copy [bool, default False] Make a copy of input ndarray.

name [label, default None] Name to be stored in the index.

See also:

Index The base pandas Index type.
TimedeltaIndex Index of timedelta64 data.
PeriodIndex Index of Period data.
to_datetime Convert argument to datetime.

date_range Create a fixed-frequency DatetimeIndex.

Notes

To learn more about the frequency strings, please see this link.

Attributes

year	The year of the datetime.
month	The month as January=1, December=12.
day	The day of the datetime.
hour	The hours of the datetime.
minute	The minutes of the datetime.
second	The seconds of the datetime.
microsecond	The microseconds of the datetime.
nanosecond	The nanoseconds of the datetime.
date	Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).
time	Returns numpy array of datetime.time.
timetz	Returns numpy array of datetime.time also containing timezone information.
dayofyear	The ordinal day of the year.
day_of_year	The ordinal day of the year.
weekofyear	(DEPRECATED) The week ordinal of the year.
week	(DEPRECATED) The week ordinal of the year.
dayofweek	The day of the week with Monday=0, Sunday=6.
day_of_week	The day of the week with Monday=0, Sunday=6.
weekday	The day of the week with Monday=0, Sunday=6.
quarter	The quarter of the date.
tz	Return timezone, if any.
freq	Return the frequency object if it is set, otherwise None.
freqstr	Return the frequency object as a string if its set, otherwise None.
is_month_start	Indicates whether the date is the first day of the month.
is_month_end	Indicates whether the date is the last day of the month.
is_quarter_start	Indicator for whether the date is the first day of a quarter.
is_quarter_end	Indicator for whether the date is the last day of a quarter.
is_year_start	Indicate whether the date is the first day of a year.
is_year_end	Indicate whether the date is the last day of the year.
is_leap_year	Boolean indicator if the date belongs to a leap year.
inferred_freq	Tries to return a string representing a frequency guess, generated by infer_freq.

pandas.DatetimeIndex.year

property DatetimeIndex.**year**
The year of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="Y")
... )
>>> datetime_series
0   2000-12-31
1   2001-12-31
2   2002-12-31
dtype: datetime64[ns]
>>> datetime_series.dt.year
0    2000
1    2001
2    2002
dtype: int64
```

pandas.DatetimeIndex.month

property DatetimeIndex.**month**
The month as January=1, December=12.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="M")
... )
>>> datetime_series
0   2000-01-31
1   2000-02-29
2   2000-03-31
dtype: datetime64[ns]
>>> datetime_series.dt.month
0    1
1    2
2    3
dtype: int64
```

pandas.DatetimeIndex.day

property DatetimeIndex.**day**
The day of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="D")
... )
>>> datetime_series
0   2000-01-01
1   2000-01-02
2   2000-01-03
dtype: datetime64[ns]
>>> datetime_series.dt.day
0    1
1    2
2    3
dtype: int64
```

pandas.DatetimeIndex.hour

property DatetimeIndex.**hour**
The hours of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="h")
... )
>>> datetime_series
0   2000-01-01 00:00:00
1   2000-01-01 01:00:00
2   2000-01-01 02:00:00
dtype: datetime64[ns]
>>> datetime_series.dt.hour
0    0
1    1
2    2
dtype: int64
```

pandas.DatetimeIndex.minute

property DatetimeIndex.**minute**
The minutes of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="T")
... )
>>> datetime_series
0   2000-01-01 00:00:00
1   2000-01-01 00:01:00
2   2000-01-01 00:02:00
dtype: datetime64[ns]
>>> datetime_series.dt.minute
0    0
1    1
2    2
dtype: int64
```

pandas.DatetimeIndex.second

property DatetimeIndex.**second**
The seconds of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="s")
... )
>>> datetime_series
0   2000-01-01 00:00:00
1   2000-01-01 00:00:01
2   2000-01-01 00:00:02
dtype: datetime64[ns]
>>> datetime_series.dt.second
0    0
1    1
2    2
dtype: int64
```

pandas.DatetimeIndex.microsecond

property DatetimeIndex.**microsecond**
The microseconds of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="us")
... )
>>> datetime_series
0   2000-01-01 00:00:00.000000
1   2000-01-01 00:00:00.000001
2   2000-01-01 00:00:00.000002
dtype: datetime64[ns]
>>> datetime_series.dt.microsecond
0       0
1       1
2       2
dtype: int64
```

pandas.DatetimeIndex.nanosecond

property DatetimeIndex.**nanosecond**
The nanoseconds of the datetime.

Examples

```
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="ns")
... )
>>> datetime_series
0   2000-01-01 00:00:00.000000000
1   2000-01-01 00:00:00.000000001
2   2000-01-01 00:00:00.000000002
dtype: datetime64[ns]
>>> datetime_series.dt.nanosecond
0       0
1       1
2       2
dtype: int64
```

pandas.DatetimeIndex.date

property DatetimeIndex.**date**
Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).

pandas.DatetimeIndex.time

property DatetimeIndex.**time**
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.DatetimeIndex.timetz

property DatetimeIndex.**timetz**
Returns numpy array of datetime.time also containing timezone information. The time part of the Timestamps.

pandas.DatetimeIndex.dayofyear

property DatetimeIndex.**dayofyear**
The ordinal day of the year.

pandas.DatetimeIndex.day_of_year

property DatetimeIndex.**day_of_year**
The ordinal day of the year.

pandas.DatetimeIndex.weekofyear

property DatetimeIndex.**weekofyear**
The week ordinal of the year.

Deprecated since version 1.1.0.

weekofyear and week have been deprecated. Please use DatetimeIndex.isocalendar().week instead.

pandas.DatetimeIndex.week

property DatetimeIndex.**week**
The week ordinal of the year.

Deprecated since version 1.1.0.

weekofyear and week have been deprecated. Please use DatetimeIndex.isocalendar().week instead.

pandas.DatetimeIndex.dayofweek

property DatetimeIndex.**dayofweek**

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the *dt* accessor) or DatetimeIndex.

Returns

Series or Index Containing integers indicating the day number.

See also:

Series.dt.dayofweek Alias.

Series.dt.weekday Alias.

Series.dt.day_name Returns the name of the day of the week.

Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

pandas.DatetimeIndex.day_of_week

property DatetimeIndex.**day_of_week**

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the *dt* accessor) or DatetimeIndex.

Returns

Series or Index Containing integers indicating the day number.

See also:

Series.dt.dayofweek Alias.

Series.dt.weekday Alias.

Series.dt.day_name Returns the name of the day of the week.

Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

pandas.DatetimeIndex.weekday

property DatetimeIndex.**weekday**

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the *dt* accessor) or DatetimeIndex.

Returns

Series or Index Containing integers indicating the day number.

See also:

Series.dt.dayofweek Alias.

Series.dt.weekday Alias.

Series.dt.day_name Returns the name of the day of the week.

Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

pandas.DatetimeIndex.quarter

property DatetimeIndex.**quarter**
The quarter of the date.

pandas.DatetimeIndex.tz

property DatetimeIndex.**tz**
Return timezone, if any.

Returns

datetime.tzinfo, pytz.tzinfo.BaseTZInfo, dateutil.tz.tz.tzfile, or None Returns None when the array is tz-naive.

pandas.DatetimeIndex.freq

property DatetimeIndex.**freq**
Return the frequency object if it is set, otherwise None.

pandas.DatetimeIndex.freqstr

property DatetimeIndex.**freqstr**
Return the frequency object as a string if its set, otherwise None.

pandas.DatetimeIndex.is_month_start

property DatetimeIndex.**is_month_start**
Indicates whether the date is the first day of the month.

Returns

Series or array For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

See also:

is_month_start Return a boolean indicating whether the date is the first day of the month.

is_month_end Return a boolean indicating whether the date is the last day of the month.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0   2018-02-27
1   2018-02-28
2   2018-03-01
dtype: datetime64[ns]
```

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```
>>> s.dt.is_month_start
0    False
1    False
2    True
dtype: bool
>>> s.dt.is_month_end
0    False
1    True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

pandas.DatetimeIndex.is_month_end

property DatetimeIndex.**is_month_end**

Indicates whether the date is the last day of the month.

Returns

Series or array For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

See also:

is_month_start Return a boolean indicating whether the date is the first day of the month.

is_month_end Return a boolean indicating whether the date is the last day of the month.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0   2018-02-27
1   2018-02-28
2   2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0    False
1    False
2    True
dtype: bool
>>> s.dt.is_month_end
0    False
1    True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

pandas.DatetimeIndex.is_quarter_start

property DatetimeIndex.**is_quarter_start**

Indicator for whether the date is the first day of a quarter.

Returns

is_quarter_start [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.

is_quarter_end Similar property for indicating the quarter start.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                   periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...           is_quarter_start=df.dates.dt.is_quarter_start)
       dates  quarter  is_quarter_start
0 2017-03-30        1             False
1 2017-03-31        1             False
2 2017-04-01        2              True
3 2017-04-02        2             False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_start
array([False, False,  True, False])
```

pandas.DatetimeIndex.is_quarter_end

property DatetimeIndex.**is_quarter_end**

Indicator for whether the date is the last day of a quarter.

Returns

is_quarter_end [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter Return the quarter of the date.

is_quarter_start Similar property indicating the quarter start.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                   periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...           is_quarter_end=df.dates.dt.is_quarter_end)
       dates  quarter    is_quarter_end
0 2017-03-30        1             False
1 2017-03-31        1              True
2 2017-04-01        2             False
3 2017-04-02        2             False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_end
array([False,  True, False, False])
```

pandas.DatetimeIndex.is_year_start

property DatetimeIndex.**is_year_start**

Indicate whether the date is the first day of a year.

Returns

Series or DatetimeIndex The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

is_year_end Similar property indicating the last day of the year.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0   2017-12-30
1   2017-12-31
2   2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_start
0    False
1    False
2    True
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_start
array([False, False,  True])
```

pandas.DatetimeIndex.is_year_end

property DatetimeIndex.**is_year_end**

Indicate whether the date is the last day of the year.

Returns

Series or DatetimeIndex The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

is_year_start Similar property indicating the start of the year.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0   2017-12-30
1   2017-12-31
2   2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_end
0    False
1     True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
              dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_end
array([False,  True, False])
```

pandas.DatetimeIndex.is_leap_year

property DatetimeIndex.**is_leap_year**

Boolean indicator if the date belongs to a leap year.

A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not by 400.

Returns

Series or ndarray Booleans indicating if dates belong to a leap year.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
DatetimeIndex(['2012-12-31', '2013-12-31', '2014-12-31'],
              dtype='datetime64[ns]', freq='A-DEC')
>>> idx.is_leap_year
array([ True, False, False])
```

```
>>> dates_series = pd.Series(idx)
>>> dates_series
0   2012-12-31
1   2013-12-31
2   2014-12-31
dtype: datetime64[ns]
>>> dates_series.dt.is_leap_year
0     True
1    False
2    False
dtype: bool
```

pandas.DatetimeIndex.inferred_freq

DatetimeIndex.**inferred_freq: Optional[str]**

Tries to return a string representing a frequency guess, generated by infer_freq. Returns None if it can't autodetect the frequency.

Methods

normalize(*args, **kwargs)	Convert times to midnight.
strftime(*args, **kwargs)	Convert to Index using specified date_format.
snap([freq])	Snap time stamps to nearest occurring frequency.
tz_convert(tz)	Convert tz-aware Datetime Array/Index from one time zone to another.
tz_localize(tz[, ambiguous, nonexistent])	Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.
round(*args, **kwargs)	Perform round operation on the data to the specified *freq*.
floor(*args, **kwargs)	Perform floor operation on the data to the specified *freq*.
ceil(*args, **kwargs)	Perform ceil operation on the data to the specified *freq*.
to_period(*args, **kwargs)	Cast to PeriodArray/Index at a particular frequency.
to_perioddelta(freq)	Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq.
to_pydatetime(*args, **kwargs)	Return Datetime Array/Index as object ndarray of datetime.datetime objects.
to_series([keep_tz, index, name])	Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.
to_frame([index, name])	Create a DataFrame with a column containing the Index.
month_name(*args, **kwargs)	Return the month names of the DateTimeIndex with specified locale.
day_name(*args, **kwargs)	Return the day names of the DateTimeIndex with specified locale.
mean(*args, **kwargs)	Return the mean value of the Array.

pandas.DatetimeIndex.normalize

DatetimeIndex.**normalize**(**args*, ***kwargs*)

Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the `.dt` accessor, and directly on Datetime Array/Index.

Returns

DatetimeArray, DatetimeIndex or Series The same type as the original data. Series

will have the same name and index. DatetimeIndex will have the same name.

See also:

floor Floor the datetimes to the specified freq.

ceil Ceil the datetimes to the specified freq.

round Round the datetimes to the specified freq.

Examples

```
>>> idx = pd.date_range(start='2014-08-01 10:00', freq='H',
...                     periods=3, tz='Asia/Calcutta')
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
               '2014-08-01 11:00:00+05:30',
               '2014-08-01 12:00:00+05:30'],
                dtype='datetime64[ns, Asia/Calcutta]', freq='H')
>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30'],
              dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

pandas.DatetimeIndex.strftime

DatetimeIndex.**strftime**(**args*, ***kwargs*)

Convert to Index using specified date_format.

Return an Index of formatted strings specified by date_format, which supports the same string format as the python standard library. Details of the string format can be found in python string format doc.

Parameters

date_format [str] Date format string (e.g. "%Y-%m-%d").

Returns

ndarray NumPy ndarray of formatted strings.

See also:

to_datetime Convert the given argument to datetime.

DatetimeIndex.normalize Return DatetimeIndex with times to midnight.

DatetimeIndex.round Round the DatetimeIndex to the specified freq.

DatetimeIndex.floor Floor the DatetimeIndex to the specified freq.

Examples

```
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                     periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
       'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

pandas.DatetimeIndex.snap

DatetimeIndex.**snap**(*freq='S'*)

Snap time stamps to nearest occurring frequency.

Returns

DatetimeIndex

pandas.DatetimeIndex.tz_convert

DatetimeIndex.**tz_convert**(*tz*)

Convert tz-aware Datetime Array/Index from one time zone to another.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time. Corresponding timestamps would be converted to this time zone of the Datetime Array/Index. A *tz* of None will convert to UTC and remove the timezone information.

Returns

Array or Index

Raises

TypeError If Datetime Array/Index is tz-naive.

See also:

DatetimeIndex.tz A timezone that has a variable offset from UTC.

DatetimeIndex.tz_localize Localize tz-naive DatetimeIndex to a given time zone, or remove timezone from a tz-aware DatetimeIndex.

Examples

With the *tz* parameter, we can change the DatetimeIndex to other time zones:

```
>>> dti = pd.date_range(start='2014-08-01 09:00',
...                     freq='H', periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
              dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
               '2014-08-01 03:00:00-05:00',
               '2014-08-01 04:00:00-05:00'],
              dtype='datetime64[ns, US/Central]', freq='H')
```

With the `tz=None`, we can remove the timezone (after converting to UTC if necessary):

```
>>> dti = pd.date_range(start='2014-08-01 09:00', freq='H',
...                     periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
               dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
               '2014-08-01 08:00:00',
               '2014-08-01 09:00:00'],
               dtype='datetime64[ns]', freq='H')
```

pandas.DatetimeIndex.tz_localize

DatetimeIndex.**tz_localize**(*tz*, *ambiguous='raise'*, *nonexistent='raise'*)

Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.

This method takes a time zone (tz) naive Datetime Array/Index object and makes this time zone aware. It does not move the time to another time zone. Time zone localization helps to switch from time zone aware to time zone unaware objects.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone to convert timestamps to. Passing `None` will remove the time zone information preserving local time.

ambiguous ['infer', 'NaT', bool array, default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

nonexistent ['shift_forward', 'shift_backward, 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time

- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

Same type as self Array/Index converted to the specified time zone.

Raises

TypeError If the Datetime Array/Index is tz-aware and tz is not None.

See also:

DatetimeIndex.tz_convert Convert tz-aware DatetimeIndex from one time zone to another.

Examples

```
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq='D')
```

Localize DatetimeIndex in US/Eastern time zone:

```
>>> tz_aware = tz_naive.tz_localize(tz='US/Eastern')
>>> tz_aware
DatetimeIndex(['2018-03-01 09:00:00-05:00',
               '2018-03-02 09:00:00-05:00',
               '2018-03-03 09:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

With the `tz=None`, we can remove the time zone information while keeping the local time (not converted to UTC):

```
>>> tz_aware.tz_localize(None)
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:30:00',
...                               '2018-10-28 02:00:00',
...                               '2018-10-28 02:30:00',
...                               '2018-10-28 02:00:00',
...                               '2018-10-28 02:30:00',
...                               '2018-10-28 03:00:00',
...                               '2018-10-28 03:30:00']))
>>> s.dt.tz_localize('CET', ambiguous='infer')
0   2018-10-28 01:30:00+02:00
```

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```
1   2018-10-28 02:00:00+02:00
2   2018-10-28 02:30:00+02:00
3   2018-10-28 02:00:00+01:00
4   2018-10-28 02:30:00+01:00
5   2018-10-28 03:00:00+01:00
6   2018-10-28 03:30:00+01:00
dtype: datetime64[ns, CET]
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:20:00',
...                               '2018-10-28 02:36:00',
...                               '2018-10-28 03:46:00']))
>>> s.dt.tz_localize('CET', ambiguous=np.array([True, True, False]))
0   2018-10-28 01:20:00+02:00
1   2018-10-28 02:36:00+02:00
2   2018-10-28 03:46:00+01:00
dtype: datetime64[ns, CET]
```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a timedelta object or *'shift_forward'* or *'shift_backwards'*.

```
>>> s = pd.to_datetime(pd.Series(['2015-03-29 02:30:00',
...                               '2015-03-29 03:30:00']))
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
0   2015-03-29 03:00:00+02:00
1   2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]
```

```
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
0   2015-03-29 01:59:59.999999999+01:00
1   2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]
```

```
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
0   2015-03-29 03:30:00+02:00
1   2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]
```

pandas.DatetimeIndex.round

DatetimeIndex.**round**(**args*, ***kwargs*)

Perform round operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to round the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order

- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.round("H")
0   2018-01-01 12:00:00
1   2018-01-01 12:00:00
2   2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.DatetimeIndex.floor

DatetimeIndex.**floor**(**args*, ***kwargs*)

Perform floor operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
```

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```
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.floor("H")
0   2018-01-01 11:00:00
1   2018-01-01 12:00:00
2   2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.DatetimeIndex.ceil

DatetimeIndex.**ceil**(**args*, ***kwargs*)

Perform ceil operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.ceil("H")
0   2018-01-01 12:00:00
1   2018-01-01 12:00:00
2   2018-01-01 13:00:00
dtype: datetime64[ns]
```

pandas.DatetimeIndex.to_period

DatetimeIndex.**to_period**(**args*, ***kwargs*)

Cast to PeriodArray/Index at a particular frequency.

Converts DatetimeArray/Index to PeriodArray/Index.

Parameters

freq [str or Offset, optional] One of pandas' *offset strings* or an Offset object. Will be inferred by default.

Returns

PeriodArray/Index

Raises

ValueError When converting a DatetimeArray/Index with non-regular values, so that a frequency cannot be inferred.

See also:

PeriodIndex Immutable ndarray holding ordinal values.

DatetimeIndex.to_pydatetime Return DatetimeIndex as object.

Examples

```
>>> df = pd.DataFrame({"y": [1, 2, 3]},
...                   index=pd.to_datetime(["2000-03-31 00:00:00",
...                                         "2000-05-31 00:00:00",
...                                         "2000-08-31 00:00:00"]))
>>> df.index.to_period("M")
PeriodIndex(['2000-03', '2000-05', '2000-08'],
            dtype='period[M]', freq='M')
```

Infer the daily frequency

```
>>> idx = pd.date_range("2017-01-01", periods=2)
>>> idx.to_period()
PeriodIndex(['2017-01-01', '2017-01-02'],
            dtype='period[D]', freq='D')
```

pandas.DatetimeIndex.to_perioddelta

DatetimeIndex.**to_perioddelta**(*freq*)

Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq. Used for vectorized offsets.

Parameters

freq [Period frequency]

Returns

TimedeltaArray/Index

pandas.DatetimeIndex.to_pydatetime

DatetimeIndex.**to_pydatetime**(**args*, ***kwargs*)

Return Datetime Array/Index as object ndarray of datetime.datetime objects.

Returns

datetimes [ndarray]

pandas.DatetimeIndex.to_series

DatetimeIndex.**to_series**(*keep_tz=<object object>*, *index=None*, *name=None*)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.

Parameters

keep_tz [optional, defaults True] Return the data keeping the timezone.

If keep_tz is True:

If the timezone is not set, the resulting Series will have a datetime64[ns] dtype.

Otherwise the Series will have an datetime64[ns, tz] dtype; the tz will be preserved.

If keep_tz is False:

Series will have a datetime64[ns] dtype. TZ aware objects will have the tz removed.

Changed in version 1.0.0: The default value is now True. In a future version, this keyword will be removed entirely. Stop passing the argument to obtain the future behavior and silence the warning.

index [Index, optional] Index of resulting Series. If None, defaults to original index.

name [str, optional] Name of resulting Series. If None, defaults to name of original index.

Returns

Series

pandas.DatetimeIndex.to_frame

DatetimeIndex.**to_frame**(*index=True*, *name=None*)

Create a DataFrame with a column containing the Index.

New in version 0.24.0.

Parameters

index [bool, default True] Set the index of the returned DataFrame as the original Index.

name [object, default None] The passed name should substitute for the index name (if it has one).

Returns

DataFrame DataFrame containing the original Index data.

See also:

Index.to_series Convert an Index to a Series.

Series.to_frame Convert Series to DataFrame.

Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
       animal
animal
Ant       Ant
Bear     Bear
Cow       Cow
```

By default, the original Index is reused. To enforce a new Index:

```
>>> idx.to_frame(index=False)
    animal
0   Ant
1  Bear
2   Cow
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_frame(index=False, name='zoo')
    zoo
0   Ant
1  Bear
2   Cow
```

pandas.DatetimeIndex.month_name

DatetimeIndex.**month_name**(**args*, ***kwargs*)

Return the month names of the DateTimeIndex with specified locale.

Parameters

locale [str, optional] Locale determining the language in which to return the month name. Default is English locale.

Returns

Index Index of month names.

Examples

```
>>> idx = pd.date_range(start='2018-01', freq='M', periods=3)
>>> idx
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31'],
              dtype='datetime64[ns]', freq='M')
>>> idx.month_name()
Index(['January', 'February', 'March'], dtype='object')
```

pandas.DatetimeIndex.day_name

DatetimeIndex.**day_name**(**args*, ***kwargs*)

Return the day names of the DateTimeIndex with specified locale.

Parameters

locale [str, optional] Locale determining the language in which to return the day name. Default is English locale.

Returns

Index Index of day names.

Examples

```
>>> idx = pd.date_range(start='2018-01-01', freq='D', periods=3)
>>> idx
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03'],
              dtype='datetime64[ns]', freq='D')
>>> idx.day_name()
Index(['Monday', 'Tuesday', 'Wednesday'], dtype='object')
```

pandas.DatetimeIndex.mean

DatetimeIndex.**mean**(**args*, ***kwargs*)

Return the mean value of the Array.

New in version 0.25.0.

Parameters

skipna [bool, default True] Whether to ignore any NaT elements.

axis [int, optional, default 0]

Returns

scalar Timestamp or Timedelta.

See also:

numpy.ndarray.mean Returns the average of array elements along a given axis.

Series.mean Return the mean value in a Series.

Notes

mean is only defined for Datetime and Timedelta dtypes, not for Period.

std	

Time/date components

DatetimeIndex.year	The year of the datetime.
DatetimeIndex.month	The month as January=1, December=12.
DatetimeIndex.day	The day of the datetime.
DatetimeIndex.hour	The hours of the datetime.
DatetimeIndex.minute	The minutes of the datetime.
DatetimeIndex.second	The seconds of the datetime.
DatetimeIndex.microsecond	The microseconds of the datetime.
DatetimeIndex.nanosecond	The nanoseconds of the datetime.
DatetimeIndex.date	Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).
DatetimeIndex.time	Returns numpy array of datetime.time.

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DatetimeIndex.timetz	Returns numpy array of datetime.time also containing timezone information.
DatetimeIndex.dayofyear	The ordinal day of the year.
DatetimeIndex.day_of_year	The ordinal day of the year.
DatetimeIndex.weekofyear	(DEPRECATED) The week ordinal of the year.
DatetimeIndex.week	(DEPRECATED) The week ordinal of the year.
DatetimeIndex.dayofweek	The day of the week with Monday=0, Sunday=6.
DatetimeIndex.day_of_week	The day of the week with Monday=0, Sunday=6.
DatetimeIndex.weekday	The day of the week with Monday=0, Sunday=6.
DatetimeIndex.quarter	The quarter of the date.
DatetimeIndex.tz	Return timezone, if any.
DatetimeIndex.freq	Return the frequency object if it is set, otherwise None.
DatetimeIndex.freqstr	Return the frequency object as a string if its set, otherwise None.
DatetimeIndex.is_month_start	Indicates whether the date is the first day of the month.
DatetimeIndex.is_month_end	Indicates whether the date is the last day of the month.
DatetimeIndex.is_quarter_start	Indicator for whether the date is the first day of a quarter.
DatetimeIndex.is_quarter_end	Indicator for whether the date is the last day of a quarter.
DatetimeIndex.is_year_start	Indicate whether the date is the first day of a year.
DatetimeIndex.is_year_end	Indicate whether the date is the last day of the year.
DatetimeIndex.is_leap_year	Boolean indicator if the date belongs to a leap year.
DatetimeIndex.inferred_freq	Tries to return a string representing a frequency guess, generated by infer_freq.

Selecting

DatetimeIndex.indexer_at_time(time[, asof])	Return index locations of values at particular time of day (e.g.
DatetimeIndex.indexer_between_time(...[, ...])	Return index locations of values between particular times of day (e.g., 9:00-9:30AM).

pandas.DatetimeIndex.indexer_at_time

DatetimeIndex.**indexer_at_time**(*time*, *asof=False*)

Return index locations of values at particular time of day (e.g. 9:30AM).

Parameters

time [datetime.time or str] Time passed in either as object (datetime.time) or as string in appropriate format ("%H:%M", "%H%M", "%I:%M%p", "%I%M%p", "%H:%M:%S", "%H%M%S", "%I:%M:%S%p", "%I%M%S%p").

Returns

values_at_time [array of integers]

See also:

indexer_between_time Get index locations of values between particular times of day.
DataFrame.at_time Select values at particular time of day.

pandas.DatetimeIndex.indexer_between_time

DatetimeIndex.**indexer_between_time**(*start_time*, *end_time*, *include_start=True*, *include_end=True*)

Return index locations of values between particular times of day (e.g., 9:00-9:30AM).

Parameters

start_time, end_time [datetime.time, str] Time passed either as object (datetime.time) or as string in appropriate format ("%H:%M", "%H%M", "%I:%M%p", "%I%M%p", "%H:%M:%S", "%H%M%S", "%I:%M:%S%p","%I%M%S%p").

include_start [bool, default True]

include_end [bool, default True]

Returns

values_between_time [array of integers]

See also:

indexer_at_time Get index locations of values at particular time of day.
DataFrame.between_time Select values between particular times of day.

Time-specific operations

DatetimeIndex.normalize(*args, **kwargs)	Convert times to midnight.
DatetimeIndex.strftime(*args, **kwargs)	Convert to Index using specified date_format.
DatetimeIndex.snap([freq])	Snap time stamps to nearest occurring frequency.
DatetimeIndex.tz_convert(tz)	Convert tz-aware Datetime Array/Index from one time zone to another.
DatetimeIndex.tz_localize(tz[, ambiguous, ...])	Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.
DatetimeIndex.round(*args, **kwargs)	Perform round operation on the data to the specified *freq*.
DatetimeIndex.floor(*args, **kwargs)	Perform floor operation on the data to the specified *freq*.
DatetimeIndex.ceil(*args, **kwargs)	Perform ceil operation on the data to the specified *freq*.
DatetimeIndex.month_name(*args, **kwargs)	Return the month names of the DateTimeIndex with specified locale.
DatetimeIndex.day_name(*args, **kwargs)	Return the day names of the DateTimeIndex with specified locale.

Conversion

DatetimeIndex.to_period(*args, **kwargs)	Cast to PeriodArray/Index at a particular frequency.
DatetimeIndex.to_perioddelta(freq)	Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq.
DatetimeIndex.to_pydatetime(*args, **kwargs)	Return Datetime Array/Index as object ndarray of datetime.datetime objects.
DatetimeIndex.to_series([keep_tz, index, name])	Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.

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DatetimeIndex.to_frame([index, name])	Create a DataFrame with a column containing the Index.

Methods

DatetimeIndex.mean(*args, **kwargs)	Return the mean value of the Array.

3.6.7 TimedeltaIndex

TimedeltaIndex([data, unit, freq, closed, ...])	Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects.

pandas.TimedeltaIndex

class pandas.**TimedeltaIndex**(*data=None*, *unit=None*, *freq=<object object>*, *closed=None*, *dtype=dtype('<m8[ns]')*, *copy=False*, *name=None*)

Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects.

Parameters

data [array-like (1-dimensional), optional] Optional timedelta-like data to construct index with.

unit [unit of the arg (D,h,m,s,ms,us,ns) denote the unit, optional] Which is an integer/float number.

freq [str or pandas offset object, optional] One of pandas date offset strings or corresponding objects. The string 'infer' can be passed in order to set the frequency of the index as the inferred frequency upon creation.

copy [bool] Make a copy of input ndarray.

name [object] Name to be stored in the index.

See also:

Index The base pandas Index type.
Timedelta Represents a duration between two dates or times.
DatetimeIndex Index of datetime64 data.
PeriodIndex Index of Period data.
timedelta_range Create a fixed-frequency TimedeltaIndex.

Notes

To learn more about the frequency strings, please see this link.

Attributes

days	Number of days for each element.
seconds	Number of seconds (>= 0 and less than 1 day) for each element.
microseconds	Number of microseconds (>= 0 and less than 1 second) for each element.
nanoseconds	Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
components	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.
inferred_freq	Tries to return a string representing a frequency guess, generated by infer_freq.

pandas.TimedeltaIndex.days

property TimedeltaIndex.**days**
Number of days for each element.

pandas.TimedeltaIndex.seconds

property TimedeltaIndex.**seconds**
Number of seconds (>= 0 and less than 1 day) for each element.

pandas.TimedeltaIndex.microseconds

property TimedeltaIndex.**microseconds**
Number of microseconds (>= 0 and less than 1 second) for each element.

pandas.TimedeltaIndex.nanoseconds

property TimedeltaIndex.**nanoseconds**
Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

pandas.TimedeltaIndex.components

property TimedeltaIndex.**components**

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns

a DataFrame

pandas.TimedeltaIndex.inferred_freq

TimedeltaIndex.**inferred_freq**

Tries to return a string representing a frequency guess, generated by infer_freq. Returns None if it can't autodetect the frequency.

Methods

to_pytimedelta(*args, **kwargs)	Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.
to_series([index, name])	Create a Series with both index and values equal to the index keys.
round(*args, **kwargs)	Perform round operation on the data to the specified *freq*.
floor(*args, **kwargs)	Perform floor operation on the data to the specified *freq*.
ceil(*args, **kwargs)	Perform ceil operation on the data to the specified *freq*.
to_frame([index, name])	Create a DataFrame with a column containing the Index.
mean(*args, **kwargs)	Return the mean value of the Array.

pandas.TimedeltaIndex.to_pytimedelta

TimedeltaIndex.**to_pytimedelta**(**args*, ***kwargs*)

Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.

Returns

datetimes [ndarray]

pandas.TimedeltaIndex.to_series

TimedeltaIndex.**to_series**(*index=None*, *name=None*)

Create a Series with both index and values equal to the index keys.

Useful with map for returning an indexer based on an index.

Parameters

index [Index, optional] Index of resulting Series. If None, defaults to original index.

name [str, optional] Name of resulting Series. If None, defaults to name of original index.

Returns

Series The dtype will be based on the type of the Index values.

See also:

Index.to_frame Convert an Index to a DataFrame.

Series.to_frame Convert Series to DataFrame.

Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
```

By default, the original Index and original name is reused.

```
>>> idx.to_series()
animal
Ant       Ant
Bear     Bear
Cow       Cow
Name: animal, dtype: object
```

To enforce a new Index, specify new labels to `index`:

```
>>> idx.to_series(index=[0, 1, 2])
0     Ant
1    Bear
2     Cow
Name: animal, dtype: object
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_series(name='zoo')
animal
Ant       Ant
Bear     Bear
Cow       Cow
Name: zoo, dtype: object
```

pandas.TimedeltaIndex.round

`TimedeltaIndex.`**`round`**`(*args, **kwargs)`

Perform round operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to round the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order

- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.round("H")
0   2018-01-01 12:00:00
1   2018-01-01 12:00:00
2   2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.TimedeltaIndex.floor

TimedeltaIndex.**floor**(**args*, ***kwargs*)

Perform floor operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
```

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```
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.floor("H")
0   2018-01-01 11:00:00
1   2018-01-01 12:00:00
2   2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.TimedeltaIndex.ceil

TimedeltaIndex.**ceil**(**args*, ***kwargs*)

Perform ceil operation on the data to the specified *freq*.

Parameters

freq [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See *frequency aliases* for a list of possible *freq* values.

ambiguous ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the *freq* cannot be converted.

Examples

DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```
>>> pd.Series(rng).dt.ceil("H")
0   2018-01-01 12:00:00
1   2018-01-01 12:00:00
2   2018-01-01 13:00:00
dtype: datetime64[ns]
```

pandas.TimedeltaIndex.to_frame

`TimedeltaIndex.`**`to_frame`**(*index=True*, *name=None*)

Create a DataFrame with a column containing the Index.

New in version 0.24.0.

Parameters

index [bool, default True] Set the index of the returned DataFrame as the original Index.

name [object, default None] The passed name should substitute for the index name (if it has one).

Returns

DataFrame DataFrame containing the original Index data.

See also:

Index.to_series Convert an Index to a Series.

Series.to_frame Convert Series to DataFrame.

Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
       animal
animal
Ant       Ant
Bear     Bear
Cow       Cow
```

By default, the original Index is reused. To enforce a new Index:

```
>>> idx.to_frame(index=False)
    animal
0   Ant
1  Bear
2   Cow
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_frame(index=False, name='zoo')
    zoo
0   Ant
1  Bear
2   Cow
```

pandas.TimedeltaIndex.mean

TimedeltaIndex.**mean**(**args*, ***kwargs*)

Return the mean value of the Array.

New in version 0.25.0.

Parameters

skipna [bool, default True] Whether to ignore any NaT elements.

axis [int, optional, default 0]

Returns

scalar Timestamp or Timedelta.

See also:

numpy.ndarray.mean Returns the average of array elements along a given axis.

Series.mean Return the mean value in a Series.

Notes

mean is only defined for Datetime and Timedelta dtypes, not for Period.

Components

`TimedeltaIndex.days`	Number of days for each element.
`TimedeltaIndex.seconds`	Number of seconds (>= 0 and less than 1 day) for each element.
`TimedeltaIndex.microseconds`	Number of microseconds (>= 0 and less than 1 second) for each element.
`TimedeltaIndex.nanoseconds`	Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
`TimedeltaIndex.components`	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.
`TimedeltaIndex.inferred_freq`	Tries to return a string representing a frequency guess, generated by infer_freq.

Conversion

`TimedeltaIndex.to_pytimedelta`(*args, **kwargs)	Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.
`TimedeltaIndex.to_series`([index, name])	Create a Series with both index and values equal to the index keys.
`TimedeltaIndex.round`(*args, **kwargs)	Perform round operation on the data to the specified *freq*.
`TimedeltaIndex.floor`(*args, **kwargs)	Perform floor operation on the data to the specified *freq*.
`TimedeltaIndex.ceil`(*args, **kwargs)	Perform ceil operation on the data to the specified *freq*.
`TimedeltaIndex.to_frame`([index, name])	Create a DataFrame with a column containing the Index.

Methods

`TimedeltaIndex.mean`(*args, **kwargs)	Return the mean value of the Array.

3.6.8 PeriodIndex

`PeriodIndex`([data, ordinal, freq, tz, ...])	Immutable ndarray holding ordinal values indicating regular periods in time.

pandas.PeriodIndex

class pandas.**PeriodIndex**(*data=None*, *ordinal=None*, *freq=None*, *tz=None*, *dtype=None*, *copy=False*, *name=None*, ***fields*)

Immutable ndarray holding ordinal values indicating regular periods in time.

Index keys are boxed to Period objects which carries the metadata (eg, frequency information).

Parameters

data [array-like (1d int np.ndarray or PeriodArray), optional] Optional period-like data to construct index with.

copy [bool] Make a copy of input ndarray.

freq [str or period object, optional] One of pandas period strings or corresponding objects.

year [int, array, or Series, default None]

month [int, array, or Series, default None]

quarter [int, array, or Series, default None]

day [int, array, or Series, default None]

hour [int, array, or Series, default None]

minute [int, array, or Series, default None]

second [int, array, or Series, default None]

tz [object, default None] Timezone for converting datetime64 data to Periods.

dtype [str or PeriodDtype, default None]

See also:

Index The base pandas Index type.
Period Represents a period of time.
DatetimeIndex Index with datetime64 data.
TimedeltaIndex Index of timedelta64 data.
period_range Create a fixed-frequency PeriodIndex.

Examples

```
>>> idx = pd.PeriodIndex(year=[2000, 2002], quarter=[1, 3])
>>> idx
PeriodIndex(['2000Q1', '2002Q3'], dtype='period[Q-DEC]', freq='Q-DEC')
```

Attributes

day	The days of the period.
dayofweek	The day of the week with Monday=0, Sunday=6.
day_of_week	The day of the week with Monday=0, Sunday=6.
dayofyear	The ordinal day of the year.
day_of_year	The ordinal day of the year.
days_in_month	The number of days in the month.
daysinmonth	The number of days in the month.

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freq	Return the frequency object if it is set, otherwise None.
freqstr	Return the frequency object as a string if its set, otherwise None.
hour	The hour of the period.
is_leap_year	Logical indicating if the date belongs to a leap year.
minute	The minute of the period.
month	The month as January=1, December=12.
quarter	The quarter of the date.
second	The second of the period.
week	The week ordinal of the year.
weekday	The day of the week with Monday=0, Sunday=6.
weekofyear	The week ordinal of the year.
year	The year of the period.

pandas.PeriodIndex.day

property PeriodIndex.**day**
The days of the period.

pandas.PeriodIndex.dayofweek

property PeriodIndex.**dayofweek**
The day of the week with Monday=0, Sunday=6.

pandas.PeriodIndex.day_of_week

property PeriodIndex.**day_of_week**
The day of the week with Monday=0, Sunday=6.

pandas.PeriodIndex.dayofyear

property PeriodIndex.**dayofyear**
The ordinal day of the year.

pandas.PeriodIndex.day_of_year

property PeriodIndex.**day_of_year**
The ordinal day of the year.

pandas.PeriodIndex.days_in_month

property PeriodIndex.**days_in_month**
The number of days in the month.

pandas.PeriodIndex.daysinmonth

property PeriodIndex.**daysinmonth**
The number of days in the month.

pandas.PeriodIndex.freq

property PeriodIndex.**freq**
Return the frequency object if it is set, otherwise None.

pandas.PeriodIndex.freqstr

property PeriodIndex.**freqstr**
Return the frequency object as a string if its set, otherwise None.

pandas.PeriodIndex.hour

property PeriodIndex.**hour**
The hour of the period.

pandas.PeriodIndex.is_leap_year

property PeriodIndex.**is_leap_year**
Logical indicating if the date belongs to a leap year.

pandas.PeriodIndex.minute

property PeriodIndex.**minute**
The minute of the period.

pandas.PeriodIndex.month

property PeriodIndex.**month**
The month as January=1, December=12.

pandas.PeriodIndex.quarter

property PeriodIndex.**quarter**
The quarter of the date.

pandas.PeriodIndex.second

property PeriodIndex.**second**
The second of the period.

pandas.PeriodIndex.week

property PeriodIndex.**week**
The week ordinal of the year.

pandas.PeriodIndex.weekday

property PeriodIndex.**weekday**
The day of the week with Monday=0, Sunday=6.

pandas.PeriodIndex.weekofyear

property PeriodIndex.**weekofyear**
The week ordinal of the year.

pandas.PeriodIndex.year

property PeriodIndex.**year**
The year of the period.

end_time	
qyear	
start_time	

Methods

asfreq([freq, how])	Convert the Period Array/Index to the specified frequency *freq*.
strftime(*args, **kwargs)	Convert to Index using specified date_format.
to_timestamp([freq, how])	Cast to DatetimeArray/Index.

pandas.PeriodIndex.asfreq

PeriodIndex.**asfreq**(*freq=None*, *how='E'*)

Convert the Period Array/Index to the specified frequency *freq*.

Parameters

freq [str] A frequency.

how [str {'E', 'S'}] Whether the elements should be aligned to the end or start within pa period.

- 'E', 'END', or 'FINISH' for end,
- 'S', 'START', or 'BEGIN' for start.

January 31st ('END') vs. January 1st ('START') for example.

Returns

Period Array/Index Constructed with the new frequency.

Examples

```
>>> pidx = pd.period_range('2010-01-01', '2015-01-01', freq='A')
>>> pidx
PeriodIndex(['2010', '2011', '2012', '2013', '2014', '2015'],
dtype='period[A-DEC]', freq='A-DEC')
```

```
>>> pidx.asfreq('M')
PeriodIndex(['2010-12', '2011-12', '2012-12', '2013-12', '2014-12',
'2015-12'], dtype='period[M]', freq='M')
```

```
>>> pidx.asfreq('M', how='S')
PeriodIndex(['2010-01', '2011-01', '2012-01', '2013-01', '2014-01',
'2015-01'], dtype='period[M]', freq='M')
```

pandas.PeriodIndex.strftime

PeriodIndex.**strftime**(**args*, ***kwargs*)

Convert to Index using specified date_format.

Return an Index of formatted strings specified by date_format, which supports the same string format as the python standard library. Details of the string format can be found in python string format doc.

Parameters

date_format [str] Date format string (e.g. "%Y-%m-%d").

Returns

ndarray NumPy ndarray of formatted strings.

See also:

to_datetime Convert the given argument to datetime.

DatetimeIndex.normalize Return DatetimeIndex with times to midnight.

DatetimeIndex.round Round the DatetimeIndex to the specified freq.

DatetimeIndex.floor Floor the DatetimeIndex to the specified freq.

Examples

```
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                     periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
       'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

pandas.PeriodIndex.to_timestamp

PeriodIndex.**to_timestamp**(*freq=None*, *how='start'*)

Cast to DatetimeArray/Index.

Parameters

freq [str or DateOffset, optional] Target frequency. The default is 'D' for week or longer, 'S' otherwise.

how [{'s', 'e', 'start', 'end'}] Whether to use the start or end of the time period being converted.

Returns

DatetimeArray/Index

Properties

PeriodIndex.day	The days of the period.
PeriodIndex.dayofweek	The day of the week with Monday=0, Sunday=6.
PeriodIndex.day_of_week	The day of the week with Monday=0, Sunday=6.
PeriodIndex.dayofyear	The ordinal day of the year.
PeriodIndex.day_of_year	The ordinal day of the year.
PeriodIndex.days_in_month	The number of days in the month.
PeriodIndex.daysinmonth	The number of days in the month.
PeriodIndex.end_time	
PeriodIndex.freq	Return the frequency object if it is set, otherwise None.
PeriodIndex.freqstr	Return the frequency object as a string if its set, otherwise None.
PeriodIndex.hour	The hour of the period.
PeriodIndex.is_leap_year	Logical indicating if the date belongs to a leap year.
PeriodIndex.minute	The minute of the period.
PeriodIndex.month	The month as January=1, December=12.
PeriodIndex.quarter	The quarter of the date.
PeriodIndex.qyear	
PeriodIndex.second	The second of the period.
PeriodIndex.start_time	
PeriodIndex.week	The week ordinal of the year.

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PeriodIndex.weekday	The day of the week with Monday=0, Sunday=6.
PeriodIndex.weekofyear	The week ordinal of the year.
PeriodIndex.year	The year of the period.

pandas.PeriodIndex.end_time

property PeriodIndex.**end_time**

pandas.PeriodIndex.qyear

property PeriodIndex.**qyear**

pandas.PeriodIndex.start_time

property PeriodIndex.**start_time**

Methods

PeriodIndex.asfreq([freq, how])	Convert the Period Array/Index to the specified frequency *freq*.
PeriodIndex.strftime(*args, **kwargs)	Convert to Index using specified date_format.
PeriodIndex.to_timestamp([freq, how])	Cast to DatetimeArray/Index.

3.7 Date offsets

3.7.1 DateOffset

DateOffset	Standard kind of date increment used for a date range.

pandas.tseries.offsets.DateOffset

class pandas.tseries.offsets.**DateOffset**

Standard kind of date increment used for a date range.

Works exactly like relativedelta in terms of the keyword args you pass in, use of the keyword n is discouraged– you would be better off specifying n in the keywords you use, but regardless it is there for you. n is needed for DateOffset subclasses.

DateOffset work as follows. Each offset specify a set of dates that conform to the DateOffset. For example, Bday defines this set to be the set of dates that are weekdays (M-F). To test if a date is in the set of a DateOffset dateOffset we can use the is_on_offset method: dateOffset.is_on_offset(date).

If a date is not on a valid date, the rollback and rollforward methods can be used to roll the date to the nearest valid date before/after the date.

DateOffsets can be created to move dates forward a given number of valid dates. For example, Bday(2) can be

added to a date to move it two business days forward. If the date does not start on a valid date, first it is moved to a valid date. Thus pseudo code is:
def __add__(date): date = rollback(date) # does nothing if date is valid return date + <n number of periods>
When a date offset is created for a negative number of periods, the date is first rolled forward. The pseudo code is:
def __add__(date): date = rollforward(date) # does nothing is date is valid return date + <n number of periods>
Zero presents a problem. Should it roll forward or back? We arbitrarily have it rollforward:

date + BDay(0) == BDay.rollforward(date)

Since 0 is a bit weird, we suggest avoiding its use.

Parameters

n [int, default 1] The number of time periods the offset represents.

normalize [bool, default False] Whether to round the result of a DateOffset addition down to the previous midnight.

****kwds** Temporal parameter that add to or replace the offset value.

Parameters that **add** to the offset (like Timedelta):

- years
- months
- weeks
- days
- hours
- minutes
- seconds
- microseconds
- nanoseconds

Parameters that **replace** the offset value:

- year
- month
- day
- weekday
- hour
- minute
- second
- microsecond
- nanosecond.

See also:

`dateutil.relativedelta.relativedelta` The relativedelta type is designed to be applied to an existing datetime an can replace specific components of that datetime, or represents an interval of time.

Examples

```
>>> from pandas.tseries.offsets import DateOffset
>>> ts = pd.Timestamp('2017-01-01 09:10:11')
>>> ts + DateOffset(months=3)
Timestamp('2017-04-01 09:10:11')
```

```
>>> ts = pd.Timestamp('2017-01-01 09:10:11')
>>> ts + DateOffset(months=2)
Timestamp('2017-03-01 09:10:11')
```

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.DateOffset.base

DateOffset.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.DateOffset.__call__

DateOffset.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.DateOffset.rollback

DateOffset.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.DateOffset.rollforward

DateOffset.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

DateOffset.freqstr
DateOffset.kwds
DateOffset.name
DateOffset.nanos
DateOffset.normalize
DateOffset.rule_code
DateOffset.n

pandas.tseries.offsets.DateOffset.freqstr

DateOffset.**freqstr**

pandas.tseries.offsets.DateOffset.kwds

DateOffset.**kwds**

pandas.tseries.offsets.DateOffset.name

DateOffset.**name**

pandas.tseries.offsets.DateOffset.nanos

DateOffset.**nanos**

pandas.tseries.offsets.DateOffset.normalize

DateOffset.**normalize**

pandas.tseries.offsets.DateOffset.rule_code

DateOffset.**rule_code**

pandas.tseries.offsets.DateOffset.n

DateOffset.**n**

Methods

DateOffset.apply(other)	
DateOffset.apply_index(other)	
DateOffset.copy	
DateOffset.isAnchored	
DateOffset.onOffset	
DateOffset.is_anchored	
DateOffset.is_on_offset	
DateOffset.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.DateOffset.apply

DateOffset.**apply**(*other*)

pandas.tseries.offsets.DateOffset.apply_index

DateOffset.**apply_index**(*other*)

pandas.tseries.offsets.DateOffset.copy

DateOffset.**copy**()

pandas.tseries.offsets.DateOffset.isAnchored

DateOffset.**isAnchored**()

pandas.tseries.offsets.DateOffset.onOffset

DateOffset.**onOffset**()

pandas.tseries.offsets.DateOffset.is_anchored

DateOffset.**is_anchored**()

pandas.tseries.offsets.DateOffset.is_on_offset

DateOffset.**is_on_offset**()

3.7.2 BusinessDay

BusinessDay	DateOffset subclass representing possibly n business days.

pandas.tseries.offsets.BusinessDay

class pandas.tseries.offsets.**BusinessDay**

DateOffset subclass representing possibly n business days.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.
offset	Alias for self._offset.

pandas.tseries.offsets.BusinessDay.base

BusinessDay.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BusinessDay.offset

BusinessDay.**offset**
Alias for self._offset.

calendar	
freqstr	
holidays	
kwds	
n	
name	
nanos	
normalize	
rule_code	
weekmask	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BusinessDay.__call__

BusinessDay.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BusinessDay.rollback

BusinessDay.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BusinessDay.rollforward

BusinessDay.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Alias:

BDay	alias of pandas._libs.tslibs.offsets.BusinessDay

pandas.tseries.offsets.BDay

pandas.tseries.offsets.**BDay**
alias of pandas._libs.tslibs.offsets.BusinessDay

Properties

BusinessDay.freqstr
BusinessDay.kwds
BusinessDay.name
BusinessDay.nanos
BusinessDay.normalize
BusinessDay.rule_code
BusinessDay.n
BusinessDay.weekmask
BusinessDay.holidays
BusinessDay.calendar

pandas.tseries.offsets.BusinessDay.freqstr

BusinessDay.**freqstr**

pandas.tseries.offsets.BusinessDay.kwds

BusinessDay.**kwds**

pandas.tseries.offsets.BusinessDay.name

BusinessDay.**name**

pandas.tseries.offsets.BusinessDay.nanos

BusinessDay.**nanos**

pandas.tseries.offsets.BusinessDay.normalize

BusinessDay.**normalize**

pandas.tseries.offsets.BusinessDay.rule_code

BusinessDay.**rule_code**

pandas.tseries.offsets.BusinessDay.n

BusinessDay.**n**

pandas.tseries.offsets.BusinessDay.weekmask

BusinessDay.**weekmask**

pandas.tseries.offsets.BusinessDay.holidays

BusinessDay.**holidays**

pandas.tseries.offsets.BusinessDay.calendar

BusinessDay.**calendar**

Methods

BusinessDay.apply(other)	
BusinessDay.apply_index(other)	
BusinessDay.copy	
BusinessDay.isAnchored	
BusinessDay.onOffset	
BusinessDay.is_anchored	
BusinessDay.is_on_offset	
BusinessDay.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BusinessDay.apply

BusinessDay.**apply**(*other*)

pandas.tseries.offsets.BusinessDay.apply_index

BusinessDay.**apply_index**(*other*)

pandas.tseries.offsets.BusinessDay.copy

BusinessDay.**copy**()

pandas.tseries.offsets.BusinessDay.isAnchored

BusinessDay.**isAnchored**()

pandas.tseries.offsets.BusinessDay.onOffset

BusinessDay.**onOffset**()

pandas.tseries.offsets.BusinessDay.is_anchored

BusinessDay.**is_anchored**()

pandas.tseries.offsets.BusinessDay.is_on_offset

BusinessDay.**is_on_offset**()

3.7.3 BusinessHour

BusinessHour	DateOffset subclass representing possibly n business hours.

pandas.tseries.offsets.BusinessHour

class pandas.tseries.offsets.**BusinessHour**

DateOffset subclass representing possibly n business hours.

Parameters

n [int, default 1] The number of months represented.

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

weekmask [str, Default 'Mon Tue Wed Thu Fri'] Weekmask of valid business days, passed to `numpy.busdaycalendar`.

start [str, default "09:00"] Start time of your custom business hour in 24h format.

end [str, default: "17:00"] End time of your custom business hour in 24h format.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.
next_bday	Used for moving to next business day.
offset	Alias for self._offset.

pandas.tseries.offsets.BusinessHour.base

BusinessHour.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BusinessHour.next_bday

BusinessHour.**next_bday**
Used for moving to next business day.

pandas.tseries.offsets.BusinessHour.offset

BusinessHour.**offset**
Alias for self._offset.

calendar	
end	
freqstr	
holidays	
kwds	
n	
name	
nanos	
normalize	
rule_code	
start	
weekmask	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback(other)	Roll provided date backward to next offset only if not on offset.
rollforward(other)	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BusinessHour.__call__

BusinessHour.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BusinessHour.rollback

BusinessHour.**rollback**(*other*)

Roll provided date backward to next offset only if not on offset.

pandas.tseries.offsets.BusinessHour.rollforward

BusinessHour.**rollforward**(*other*)

Roll provided date forward to next offset only if not on offset.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

BusinessHour.freqstr
BusinessHour.kwds
BusinessHour.name
BusinessHour.nanos
BusinessHour.normalize
BusinessHour.rule_code
BusinessHour.n
BusinessHour.start
BusinessHour.end
BusinessHour.weekmask
BusinessHour.holidays
BusinessHour.calendar

pandas.tseries.offsets.BusinessHour.freqstr

BusinessHour.**freqstr**

pandas.tseries.offsets.BusinessHour.kwds

BusinessHour.**kwds**

pandas.tseries.offsets.BusinessHour.name

BusinessHour.**name**

pandas.tseries.offsets.BusinessHour.nanos

BusinessHour.**nanos**

pandas.tseries.offsets.BusinessHour.normalize

BusinessHour.**normalize**

pandas.tseries.offsets.BusinessHour.rule_code

BusinessHour.**rule_code**

pandas.tseries.offsets.BusinessHour.n

BusinessHour.**n**

pandas.tseries.offsets.BusinessHour.start

BusinessHour.**start**

pandas.tseries.offsets.BusinessHour.end

BusinessHour.**end**

pandas.tseries.offsets.BusinessHour.weekmask

BusinessHour.**weekmask**

pandas.tseries.offsets.BusinessHour.holidays

BusinessHour.**holidays**

pandas.tseries.offsets.BusinessHour.calendar

BusinessHour.**calendar**

Methods

BusinessHour.apply(other)	
BusinessHour.apply_index(other)	
BusinessHour.copy	
BusinessHour.isAnchored	
BusinessHour.onOffset	
BusinessHour.is_anchored	
BusinessHour.is_on_offset	
BusinessHour.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BusinessHour.apply

BusinessHour.**apply**(*other*)

pandas.tseries.offsets.BusinessHour.apply_index

BusinessHour.**apply_index**(*other*)

pandas.tseries.offsets.BusinessHour.copy

BusinessHour.**copy**()

pandas.tseries.offsets.BusinessHour.isAnchored

BusinessHour.**isAnchored**()

pandas.tseries.offsets.BusinessHour.onOffset

BusinessHour.**onOffset**()

pandas.tseries.offsets.BusinessHour.is_anchored

BusinessHour.**is_anchored**()

pandas.tseries.offsets.BusinessHour.is_on_offset

BusinessHour.**is_on_offset**()

3.7.4 CustomBusinessDay

CustomBusinessDay	DateOffset subclass representing custom business days excluding holidays.

pandas.tseries.offsets.CustomBusinessDay

class pandas.tseries.offsets.**CustomBusinessDay**

DateOffset subclass representing custom business days excluding holidays.

Parameters

n [int, default 1]

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

weekmask [str, Default 'Mon Tue Wed Thu Fri'] Weekmask of valid business days, passed to `numpy.busdaycalendar`.

holidays [list] List/array of dates to exclude from the set of valid business days, passed to `numpy.busdaycalendar`.

calendar [pd.HolidayCalendar or np.busdaycalendar]

offset [timedelta, default timedelta(0)]

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.
offset	Alias for self._offset.

pandas.tseries.offsets.CustomBusinessDay.base

CustomBusinessDay.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.CustomBusinessDay.offset

CustomBusinessDay.**offset**
Alias for self._offset.

calendar	
freqstr	
holidays	
kwds	
n	
name	
nanos	
normalize	
rule_code	
weekmask	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.CustomBusinessDay.__call__

CustomBusinessDay.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.CustomBusinessDay.rollback

CustomBusinessDay.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.CustomBusinessDay.rollforward

CustomBusinessDay.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Alias:

CDay	alias of pandas._libs.tslibs.offsets.CustomBusinessDay

pandas.tseries.offsets.CDay

pandas.tseries.offsets.**CDay**
alias of pandas._libs.tslibs.offsets.CustomBusinessDay

Properties

CustomBusinessDay.freqstr
CustomBusinessDay.kwds
CustomBusinessDay.name
CustomBusinessDay.nanos
CustomBusinessDay.normalize
CustomBusinessDay.rule_code
CustomBusinessDay.n
CustomBusinessDay.weekmask
CustomBusinessDay.calendar
CustomBusinessDay.holidays

pandas.tseries.offsets.CustomBusinessDay.freqstr

CustomBusinessDay.**freqstr**

pandas.tseries.offsets.CustomBusinessDay.kwds

CustomBusinessDay.**kwds**

pandas.tseries.offsets.CustomBusinessDay.name

CustomBusinessDay.**name**

pandas.tseries.offsets.CustomBusinessDay.nanos

CustomBusinessDay.**nanos**

pandas.tseries.offsets.CustomBusinessDay.normalize

CustomBusinessDay.**normalize**

pandas.tseries.offsets.CustomBusinessDay.rule_code

CustomBusinessDay.**rule_code**

pandas.tseries.offsets.CustomBusinessDay.n

CustomBusinessDay.**n**

pandas.tseries.offsets.CustomBusinessDay.weekmask

CustomBusinessDay.**weekmask**

pandas.tseries.offsets.CustomBusinessDay.calendar

CustomBusinessDay.**calendar**

pandas.tseries.offsets.CustomBusinessDay.holidays

CustomBusinessDay.**holidays**

Methods

CustomBusinessDay.apply_index	
CustomBusinessDay.apply(other)	
CustomBusinessDay.copy	
CustomBusinessDay.isAnchored	
CustomBusinessDay.onOffset	
CustomBusinessDay.is_anchored	
CustomBusinessDay.is_on_offset	
CustomBusinessDay.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.CustomBusinessDay.apply_index

CustomBusinessDay.**apply_index**()

pandas.tseries.offsets.CustomBusinessDay.apply

CustomBusinessDay.**apply**(*other*)

pandas.tseries.offsets.CustomBusinessDay.copy

CustomBusinessDay.**copy**()

pandas.tseries.offsets.CustomBusinessDay.isAnchored

CustomBusinessDay.**isAnchored**()

pandas.tseries.offsets.CustomBusinessDay.onOffset

CustomBusinessDay.**onOffset**()

pandas.tseries.offsets.CustomBusinessDay.is_anchored

CustomBusinessDay.**is_anchored**()

pandas.tseries.offsets.CustomBusinessDay.is_on_offset

CustomBusinessDay.**is_on_offset**()

3.7.5 CustomBusinessHour

CustomBusinessHour	DateOffset subclass representing possibly n custom business days.

pandas.tseries.offsets.CustomBusinessHour

class pandas.tseries.offsets.**CustomBusinessHour**

DateOffset subclass representing possibly n custom business days.

Parameters

n [int, default 1] The number of months represented.

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

weekmask [str, Default 'Mon Tue Wed Thu Fri'] Weekmask of valid business days, passed to `numpy.busdaycalendar`.

start [str, default "09:00"] Start time of your custom business hour in 24h format.

end [str, default: "17:00"] End time of your custom business hour in 24h format.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.
next_bday	Used for moving to next business day.
offset	Alias for self._offset.

pandas.tseries.offsets.CustomBusinessHour.base

CustomBusinessHour.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.CustomBusinessHour.next_bday

CustomBusinessHour.**next_bday**
Used for moving to next business day.

pandas.tseries.offsets.CustomBusinessHour.offset

CustomBusinessHour.**offset**
Alias for self._offset.

calendar	
end	
freqstr	
holidays	
kwds	
n	
name	
nanos	
normalize	
rule_code	
start	
weekmask	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback(other)	Roll provided date backward to next offset only if not on offset.
rollforward(other)	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.CustomBusinessHour.__call__

CustomBusinessHour.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.CustomBusinessHour.rollback

CustomBusinessHour.**rollback**(*other*)

Roll provided date backward to next offset only if not on offset.

pandas.tseries.offsets.CustomBusinessHour.rollforward

CustomBusinessHour.**rollforward**(*other*)

Roll provided date forward to next offset only if not on offset.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

CustomBusinessHour.freqstr
CustomBusinessHour.kwds
CustomBusinessHour.name
CustomBusinessHour.nanos
CustomBusinessHour.normalize
CustomBusinessHour.rule_code
CustomBusinessHour.n
CustomBusinessHour.weekmask
CustomBusinessHour.calendar
CustomBusinessHour.holidays
CustomBusinessHour.start
CustomBusinessHour.end

pandas.tseries.offsets.CustomBusinessHour.freqstr

CustomBusinessHour.**freqstr**

pandas.tseries.offsets.CustomBusinessHour.kwds

CustomBusinessHour.**kwds**

pandas.tseries.offsets.CustomBusinessHour.name

CustomBusinessHour.**name**

pandas.tseries.offsets.CustomBusinessHour.nanos

CustomBusinessHour.**nanos**

pandas.tseries.offsets.CustomBusinessHour.normalize

CustomBusinessHour.**normalize**

pandas.tseries.offsets.CustomBusinessHour.rule_code

CustomBusinessHour.**rule_code**

pandas.tseries.offsets.CustomBusinessHour.n

CustomBusinessHour.**n**

pandas.tseries.offsets.CustomBusinessHour.weekmask

CustomBusinessHour.**weekmask**

pandas.tseries.offsets.CustomBusinessHour.calendar

CustomBusinessHour.**calendar**

pandas.tseries.offsets.CustomBusinessHour.holidays

CustomBusinessHour.**holidays**

pandas.tseries.offsets.CustomBusinessHour.start

CustomBusinessHour.**start**

pandas.tseries.offsets.CustomBusinessHour.end

CustomBusinessHour.**end**

Methods

CustomBusinessHour.apply(other)	
CustomBusinessHour.apply_index(other)	
CustomBusinessHour.copy	
CustomBusinessHour.isAnchored	
CustomBusinessHour.onOffset	
CustomBusinessHour.is_anchored	
CustomBusinessHour.is_on_offset	
CustomBusinessHour.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.CustomBusinessHour.apply

CustomBusinessHour.**apply**(*other*)

pandas.tseries.offsets.CustomBusinessHour.apply_index

CustomBusinessHour.**apply_index**(*other*)

pandas.tseries.offsets.CustomBusinessHour.copy

CustomBusinessHour.**copy**()

pandas.tseries.offsets.CustomBusinessHour.isAnchored

CustomBusinessHour.**isAnchored**()

pandas.tseries.offsets.CustomBusinessHour.onOffset

CustomBusinessHour.**onOffset**()

pandas.tseries.offsets.CustomBusinessHour.is_anchored

CustomBusinessHour.**is_anchored**()

pandas.tseries.offsets.CustomBusinessHour.is_on_offset

CustomBusinessHour.**is_on_offset**()

3.7.6 MonthEnd

MonthEnd	DateOffset of one month end.

pandas.tseries.offsets.MonthEnd

class pandas.tseries.offsets.**MonthEnd**

DateOffset of one month end.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.MonthEnd.base

MonthEnd.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.MonthEnd.__call__

MonthEnd.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.MonthEnd.rollback

MonthEnd.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.MonthEnd.rollforward

MonthEnd.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

MonthEnd.freqstr
MonthEnd.kwds
MonthEnd.name
MonthEnd.nanos
MonthEnd.normalize
MonthEnd.rule_code
MonthEnd.n

pandas.tseries.offsets.MonthEnd.freqstr

MonthEnd.**freqstr**

pandas.tseries.offsets.MonthEnd.kwds

MonthEnd.**kwds**

pandas.tseries.offsets.MonthEnd.name

MonthEnd.**name**

pandas.tseries.offsets.MonthEnd.nanos

MonthEnd.**nanos**

pandas.tseries.offsets.MonthEnd.normalize

MonthEnd.**normalize**

pandas.tseries.offsets.MonthEnd.rule_code

MonthEnd.**rule_code**

pandas.tseries.offsets.MonthEnd.n

MonthEnd.**n**

Methods

MonthEnd.apply(other)	
MonthEnd.apply_index(other)	
MonthEnd.copy	
MonthEnd.isAnchored	
MonthEnd.onOffset	
MonthEnd.is_anchored	
MonthEnd.is_on_offset	
MonthEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.MonthEnd.apply

MonthEnd.**apply**(*other*)

pandas.tseries.offsets.MonthEnd.apply_index

MonthEnd.**apply_index**(*other*)

pandas.tseries.offsets.MonthEnd.copy

MonthEnd.**copy**()

pandas.tseries.offsets.MonthEnd.isAnchored

MonthEnd.**isAnchored**()

pandas.tseries.offsets.MonthEnd.onOffset

MonthEnd.**onOffset**()

pandas.tseries.offsets.MonthEnd.is_anchored

MonthEnd.**is_anchored**()

pandas.tseries.offsets.MonthEnd.is_on_offset

MonthEnd.**is_on_offset**()

3.7.7 MonthBegin

MonthBegin	DateOffset of one month at beginning.

pandas.tseries.offsets.MonthBegin

class pandas.tseries.offsets.**MonthBegin**

DateOffset of one month at beginning.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.MonthBegin.base

MonthBegin.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.MonthBegin.__call__

MonthBegin.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.MonthBegin.rollback

MonthBegin.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.MonthBegin.rollforward

MonthBegin.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

MonthBegin.freqstr
MonthBegin.kwds
MonthBegin.name
MonthBegin.nanos
MonthBegin.normalize
MonthBegin.rule_code
MonthBegin.n

pandas.tseries.offsets.MonthBegin.freqstr

MonthBegin.**freqstr**

pandas.tseries.offsets.MonthBegin.kwds

MonthBegin.**kwds**

pandas.tseries.offsets.MonthBegin.name

MonthBegin.**name**

pandas.tseries.offsets.MonthBegin.nanos

MonthBegin.**nanos**

pandas.tseries.offsets.MonthBegin.normalize

MonthBegin.**normalize**

pandas.tseries.offsets.MonthBegin.rule_code

MonthBegin.**rule_code**

pandas.tseries.offsets.MonthBegin.n

MonthBegin.**n**

Methods

MonthBegin.apply(other)	
MonthBegin.apply_index(other)	
MonthBegin.copy	
MonthBegin.isAnchored	
MonthBegin.onOffset	
MonthBegin.is_anchored	
MonthBegin.is_on_offset	
MonthBegin.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.MonthBegin.apply

MonthBegin.**apply**(*other*)

pandas.tseries.offsets.MonthBegin.apply_index

MonthBegin.**apply_index**(*other*)

pandas.tseries.offsets.MonthBegin.copy

MonthBegin.**copy**()

pandas.tseries.offsets.MonthBegin.isAnchored

MonthBegin.**isAnchored**()

pandas.tseries.offsets.MonthBegin.onOffset

MonthBegin.**onOffset**()

pandas.tseries.offsets.MonthBegin.is_anchored

MonthBegin.**is_anchored**()

pandas.tseries.offsets.MonthBegin.is_on_offset

MonthBegin.**is_on_offset**()

3.7.8 BusinessMonthEnd

BusinessMonthEnd	DateOffset increments between the last business day of the month

pandas.tseries.offsets.BusinessMonthEnd

class pandas.tseries.offsets.**BusinessMonthEnd**

DateOffset increments between the last business day of the month

Examples

```
>>> from pandas.tseries.offset import BMonthEnd
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BMonthEnd()
Timestamp('2020-05-29 05:01:15')
>>> ts + BMonthEnd(2)
Timestamp('2020-06-30 05:01:15')
>>> ts + BMonthEnd(-2)
Timestamp('2020-03-31 05:01:15')
```

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BusinessMonthEnd.base

BusinessMonthEnd.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BusinessMonthEnd.__call__

BusinessMonthEnd.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BusinessMonthEnd.rollback

BusinessMonthEnd.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BusinessMonthEnd.rollforward

BusinessMonthEnd.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Alias:

BMonthEnd	alias of pandas._libs.tslibs.offsets.BusinessMonthEnd

pandas.tseries.offsets.BMonthEnd

pandas.tseries.offsets.**BMonthEnd**

alias of pandas._libs.tslibs.offsets.BusinessMonthEnd

Properties

BusinessMonthEnd.freqstr
BusinessMonthEnd.kwds
BusinessMonthEnd.name
BusinessMonthEnd.nanos
BusinessMonthEnd.normalize
BusinessMonthEnd.rule_code
BusinessMonthEnd.n

pandas.tseries.offsets.BusinessMonthEnd.freqstr

BusinessMonthEnd.**freqstr**

pandas.tseries.offsets.BusinessMonthEnd.kwds

BusinessMonthEnd.**kwds**

pandas.tseries.offsets.BusinessMonthEnd.name

BusinessMonthEnd.**name**

pandas.tseries.offsets.BusinessMonthEnd.nanos

BusinessMonthEnd.**nanos**

pandas.tseries.offsets.BusinessMonthEnd.normalize

BusinessMonthEnd.**normalize**

pandas.tseries.offsets.BusinessMonthEnd.rule_code

BusinessMonthEnd.**rule_code**

pandas.tseries.offsets.BusinessMonthEnd.n

BusinessMonthEnd.**n**

Methods

BusinessMonthEnd.apply(other)	
BusinessMonthEnd.apply_index(other)	
BusinessMonthEnd.copy	
BusinessMonthEnd.isAnchored	
BusinessMonthEnd.onOffset	
BusinessMonthEnd.is_anchored	
BusinessMonthEnd.is_on_offset	
BusinessMonthEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BusinessMonthEnd.apply

BusinessMonthEnd.**apply**(*other*)

pandas.tseries.offsets.BusinessMonthEnd.apply_index

BusinessMonthEnd.**apply_index**(*other*)

pandas.tseries.offsets.BusinessMonthEnd.copy

BusinessMonthEnd.**copy**()

pandas.tseries.offsets.BusinessMonthEnd.isAnchored

BusinessMonthEnd.**isAnchored**()

pandas.tseries.offsets.BusinessMonthEnd.onOffset

BusinessMonthEnd.**onOffset**()

pandas.tseries.offsets.BusinessMonthEnd.is_anchored

BusinessMonthEnd.**is_anchored**()

pandas.tseries.offsets.BusinessMonthEnd.is_on_offset

BusinessMonthEnd.**is_on_offset**()

3.7.9 BusinessMonthBegin

BusinessMonthBegin	DateOffset of one month at the first business day.

pandas.tseries.offsets.BusinessMonthBegin

class pandas.tseries.offsets.**BusinessMonthBegin**

DateOffset of one month at the first business day.

Examples

```
>>> from pandas.tseries.offset import BMonthBegin
>>> ts=pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BMonthBegin()
Timestamp('2020-06-01 05:01:15')
>>> ts + BMonthBegin(2)
Timestamp('2020-07-01 05:01:15')
>>> ts + BMonthBegin(-3)
Timestamp('2020-03-02 05:01:15')
```

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BusinessMonthBegin.base

BusinessMonthBegin.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BusinessMonthBegin.__call__

BusinessMonthBegin.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BusinessMonthBegin.rollback

BusinessMonthBegin.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BusinessMonthBegin.rollforward

BusinessMonthBegin.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Alias:

BMonthBegin	alias of pandas._libs.tslibs.offsets.BusinessMonthBegin

pandas.tseries.offsets.BMonthBegin

pandas.tseries.offsets.**BMonthBegin**
alias of pandas._libs.tslibs.offsets.BusinessMonthBegin

Properties

BusinessMonthBegin.freqstr
BusinessMonthBegin.kwds
BusinessMonthBegin.name
BusinessMonthBegin.nanos
BusinessMonthBegin.normalize
BusinessMonthBegin.rule_code

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BusinessMonthBegin.n

pandas.tseries.offsets.BusinessMonthBegin.freqstr

BusinessMonthBegin.**freqstr**

pandas.tseries.offsets.BusinessMonthBegin.kwds

BusinessMonthBegin.**kwds**

pandas.tseries.offsets.BusinessMonthBegin.name

BusinessMonthBegin.**name**

pandas.tseries.offsets.BusinessMonthBegin.nanos

BusinessMonthBegin.**nanos**

pandas.tseries.offsets.BusinessMonthBegin.normalize

BusinessMonthBegin.**normalize**

pandas.tseries.offsets.BusinessMonthBegin.rule_code

BusinessMonthBegin.**rule_code**

pandas.tseries.offsets.BusinessMonthBegin.n

BusinessMonthBegin.**n**

Methods

BusinessMonthBegin.apply(other)	
BusinessMonthBegin.apply_index(other)	
BusinessMonthBegin.copy	
BusinessMonthBegin.isAnchored	
BusinessMonthBegin.onOffset	
BusinessMonthBegin.is_anchored	
BusinessMonthBegin.is_on_offset	
BusinessMonthBegin.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BusinessMonthBegin.apply

BusinessMonthBegin.**apply**(*other*)

pandas.tseries.offsets.BusinessMonthBegin.apply_index

BusinessMonthBegin.**apply_index**(*other*)

pandas.tseries.offsets.BusinessMonthBegin.copy

BusinessMonthBegin.**copy**()

pandas.tseries.offsets.BusinessMonthBegin.isAnchored

BusinessMonthBegin.**isAnchored**()

pandas.tseries.offsets.BusinessMonthBegin.onOffset

BusinessMonthBegin.**onOffset**()

pandas.tseries.offsets.BusinessMonthBegin.is_anchored

BusinessMonthBegin.**is_anchored**()

pandas.tseries.offsets.BusinessMonthBegin.is_on_offset

BusinessMonthBegin.**is_on_offset**()

3.7.10 CustomBusinessMonthEnd

CustomBusinessMonthEnd

Attributes

pandas.tseries.offsets.CustomBusinessMonthEnd

class pandas.tseries.offsets.**CustomBusinessMonthEnd**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.
cbday_roll	Define default roll function to be called in apply method.
month_roll	Define default roll function to be called in apply method.
offset	Alias for self._offset.

pandas.tseries.offsets.CustomBusinessMonthEnd.base

CustomBusinessMonthEnd.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.CustomBusinessMonthEnd.cbday_roll

CustomBusinessMonthEnd.**cbday_roll**
Define default roll function to be called in apply method.

pandas.tseries.offsets.CustomBusinessMonthEnd.month_roll

CustomBusinessMonthEnd.**month_roll**
Define default roll function to be called in apply method.

pandas.tseries.offsets.CustomBusinessMonthEnd.offset

CustomBusinessMonthEnd.**offset**
Alias for self._offset.

calendar	
freqstr	
holidays	
kwds	
m_offset	
n	
name	
nanos	
normalize	
rule_code	
weekmask	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.CustomBusinessMonthEnd.__call__

CustomBusinessMonthEnd.**__call__**(**args*, ***kwargs*)

Call self as a function.

pandas.tseries.offsets.CustomBusinessMonthEnd.rollback

CustomBusinessMonthEnd.**rollback**()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.CustomBusinessMonthEnd.rollforward

CustomBusinessMonthEnd.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Alias:

CBMonthEnd	alias of pandas._libs.tslibs.offsets.CustomBusinessMonthEnd

pandas.tseries.offsets.CBMonthEnd

pandas.tseries.offsets.**CBMonthEnd**
alias of pandas._libs.tslibs.offsets.CustomBusinessMonthEnd

Properties

CustomBusinessMonthEnd.freqstr
CustomBusinessMonthEnd.kwds
CustomBusinessMonthEnd.m_offset
CustomBusinessMonthEnd.name
CustomBusinessMonthEnd.nanos
CustomBusinessMonthEnd.normalize
CustomBusinessMonthEnd.rule_code
CustomBusinessMonthEnd.n
CustomBusinessMonthEnd.weekmask
CustomBusinessMonthEnd.calendar
CustomBusinessMonthEnd.holidays

pandas.tseries.offsets.CustomBusinessMonthEnd.freqstr

CustomBusinessMonthEnd.**freqstr**

pandas.tseries.offsets.CustomBusinessMonthEnd.kwds

CustomBusinessMonthEnd.**kwds**

pandas.tseries.offsets.CustomBusinessMonthEnd.m_offset

CustomBusinessMonthEnd.**m_offset**

pandas.tseries.offsets.CustomBusinessMonthEnd.name

CustomBusinessMonthEnd.**name**

pandas.tseries.offsets.CustomBusinessMonthEnd.nanos

CustomBusinessMonthEnd.**nanos**

pandas.tseries.offsets.CustomBusinessMonthEnd.normalize

CustomBusinessMonthEnd.**normalize**

pandas.tseries.offsets.CustomBusinessMonthEnd.rule_code

CustomBusinessMonthEnd.**rule_code**

pandas.tseries.offsets.CustomBusinessMonthEnd.n

CustomBusinessMonthEnd.**n**

pandas.tseries.offsets.CustomBusinessMonthEnd.weekmask

CustomBusinessMonthEnd.**weekmask**

pandas.tseries.offsets.CustomBusinessMonthEnd.calendar

CustomBusinessMonthEnd.**calendar**

pandas.tseries.offsets.CustomBusinessMonthEnd.holidays

CustomBusinessMonthEnd.**holidays**

Methods

CustomBusinessMonthEnd.apply(other)	
CustomBusinessMonthEnd.apply_index(other)	
CustomBusinessMonthEnd.copy	
CustomBusinessMonthEnd.isAnchored	
CustomBusinessMonthEnd.onOffset	
CustomBusinessMonthEnd.is_anchored	
CustomBusinessMonthEnd.is_on_offset	
CustomBusinessMonthEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.CustomBusinessMonthEnd.apply

CustomBusinessMonthEnd.**apply**(*other*)

pandas.tseries.offsets.CustomBusinessMonthEnd.apply_index

CustomBusinessMonthEnd.**apply_index**(*other*)

pandas.tseries.offsets.CustomBusinessMonthEnd.copy

CustomBusinessMonthEnd.**copy**()

pandas.tseries.offsets.CustomBusinessMonthEnd.isAnchored

CustomBusinessMonthEnd.**isAnchored**()

pandas.tseries.offsets.CustomBusinessMonthEnd.onOffset

CustomBusinessMonthEnd.**onOffset**()

pandas.tseries.offsets.CustomBusinessMonthEnd.is_anchored

CustomBusinessMonthEnd.**is_anchored**()

pandas.tseries.offsets.CustomBusinessMonthEnd.is_on_offset

CustomBusinessMonthEnd.**is_on_offset**()

3.7.11 CustomBusinessMonthBegin

CustomBusinessMonthBegin

Attributes

pandas.tseries.offsets.CustomBusinessMonthBegin

class pandas.tseries.offsets.**CustomBusinessMonthBegin**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.
cbday_roll	Define default roll function to be called in apply method.
month_roll	Define default roll function to be called in apply method.
offset	Alias for self._offset.

pandas.tseries.offsets.CustomBusinessMonthBegin.base

CustomBusinessMonthBegin.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.CustomBusinessMonthBegin.cbday_roll

CustomBusinessMonthBegin.**cbday_roll**
Define default roll function to be called in apply method.

pandas.tseries.offsets.CustomBusinessMonthBegin.month_roll

CustomBusinessMonthBegin.**month_roll**
Define default roll function to be called in apply method.

pandas.tseries.offsets.CustomBusinessMonthBegin.offset

CustomBusinessMonthBegin.**offset**
Alias for self._offset.

calendar	
freqstr	
holidays	
kwds	
m_offset	
n	
name	
nanos	
normalize	
rule_code	
weekmask	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.CustomBusinessMonthBegin.__call__

CustomBusinessMonthBegin.**__call__**(**args*, ***kwargs*)

Call self as a function.

pandas.tseries.offsets.CustomBusinessMonthBegin.rollback

CustomBusinessMonthBegin.**rollback**()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.CustomBusinessMonthBegin.rollforward

CustomBusinessMonthBegin.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Alias:

CBMonthBegin	alias of pandas._libs.tslibs.offsets.CustomBusinessMonthBegin

pandas.tseries.offsets.CBMonthBegin

pandas.tseries.offsets.**CBMonthBegin**
alias of pandas._libs.tslibs.offsets.CustomBusinessMonthBegin

Properties

CustomBusinessMonthBegin.freqstr
CustomBusinessMonthBegin.kwds
CustomBusinessMonthBegin.m_offset
CustomBusinessMonthBegin.name
CustomBusinessMonthBegin.nanos
CustomBusinessMonthBegin.normalize
CustomBusinessMonthBegin.rule_code
CustomBusinessMonthBegin.n
CustomBusinessMonthBegin.weekmask
CustomBusinessMonthBegin.calendar
CustomBusinessMonthBegin.holidays

pandas.tseries.offsets.CustomBusinessMonthBegin.freqstr

CustomBusinessMonthBegin.**freqstr**

pandas.tseries.offsets.CustomBusinessMonthBegin.kwds

CustomBusinessMonthBegin.**kwds**

pandas.tseries.offsets.CustomBusinessMonthBegin.m_offset

CustomBusinessMonthBegin.**m_offset**

pandas.tseries.offsets.CustomBusinessMonthBegin.name

CustomBusinessMonthBegin.**name**

pandas.tseries.offsets.CustomBusinessMonthBegin.nanos

CustomBusinessMonthBegin.**nanos**

pandas.tseries.offsets.CustomBusinessMonthBegin.normalize

CustomBusinessMonthBegin.**normalize**

pandas.tseries.offsets.CustomBusinessMonthBegin.rule_code

CustomBusinessMonthBegin.**rule_code**

pandas.tseries.offsets.CustomBusinessMonthBegin.n

CustomBusinessMonthBegin.**n**

pandas.tseries.offsets.CustomBusinessMonthBegin.weekmask

CustomBusinessMonthBegin.**weekmask**

pandas.tseries.offsets.CustomBusinessMonthBegin.calendar

CustomBusinessMonthBegin.**calendar**

pandas.tseries.offsets.CustomBusinessMonthBegin.holidays

CustomBusinessMonthBegin.**holidays**

Methods

CustomBusinessMonthBegin.apply(other)	
CustomBusinessMonthBegin.apply_index(other)	
CustomBusinessMonthBegin.copy	
CustomBusinessMonthBegin.isAnchored	
CustomBusinessMonthBegin.onOffset	
CustomBusinessMonthBegin.is_anchored	
CustomBusinessMonthBegin.is_on_offset	
CustomBusinessMonthBegin.__call__(*args, ...)	Call self as a function.

pandas.tseries.offsets.CustomBusinessMonthBegin.apply

CustomBusinessMonthBegin.**apply**(*other*)

pandas.tseries.offsets.CustomBusinessMonthBegin.apply_index

CustomBusinessMonthBegin.**apply_index**(*other*)

pandas.tseries.offsets.CustomBusinessMonthBegin.copy

CustomBusinessMonthBegin.**copy**()

pandas.tseries.offsets.CustomBusinessMonthBegin.isAnchored

CustomBusinessMonthBegin.**isAnchored**()

pandas.tseries.offsets.CustomBusinessMonthBegin.onOffset

CustomBusinessMonthBegin.**onOffset**()

pandas.tseries.offsets.CustomBusinessMonthBegin.is_anchored

CustomBusinessMonthBegin.**is_anchored**()

pandas.tseries.offsets.CustomBusinessMonthBegin.is_on_offset

CustomBusinessMonthBegin.**is_on_offset**()

3.7.12 SemiMonthEnd

SemiMonthEnd	Two DateOffset's per month repeating on the last day of the month and day_of_month.

pandas.tseries.offsets.SemiMonthEnd

class pandas.tseries.offsets.**SemiMonthEnd**

Two DateOffset's per month repeating on the last day of the month and day_of_month.

Parameters

n [int]

normalize [bool, default False]

day_of_month [int, {1, 3,. . . ,27}, default 15]

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.SemiMonthEnd.base

SemiMonthEnd.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

day_of_month	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.SemiMonthEnd.__call__

SemiMonthEnd.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.SemiMonthEnd.rollback

SemiMonthEnd.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.SemiMonthEnd.rollforward

SemiMonthEnd.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

SemiMonthEnd.freqstr
SemiMonthEnd.kwds
SemiMonthEnd.name
SemiMonthEnd.nanos
SemiMonthEnd.normalize
SemiMonthEnd.rule_code
SemiMonthEnd.n
SemiMonthEnd.day_of_month

pandas.tseries.offsets.SemiMonthEnd.freqstr

SemiMonthEnd.**freqstr**

pandas.tseries.offsets.SemiMonthEnd.kwds

SemiMonthEnd.**kwds**

pandas.tseries.offsets.SemiMonthEnd.name

SemiMonthEnd.**name**

pandas.tseries.offsets.SemiMonthEnd.nanos

SemiMonthEnd.**nanos**

pandas.tseries.offsets.SemiMonthEnd.normalize

SemiMonthEnd.**normalize**

pandas.tseries.offsets.SemiMonthEnd.rule_code

SemiMonthEnd.**rule_code**

pandas.tseries.offsets.SemiMonthEnd.n

SemiMonthEnd.**n**

pandas.tseries.offsets.SemiMonthEnd.day_of_month

SemiMonthEnd.**day_of_month**

Methods

SemiMonthEnd.apply(other)	
SemiMonthEnd.apply_index(other)	
SemiMonthEnd.copy	
SemiMonthEnd.isAnchored	
SemiMonthEnd.onOffset	
SemiMonthEnd.is_anchored	
SemiMonthEnd.is_on_offset	
SemiMonthEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.SemiMonthEnd.apply

SemiMonthEnd.**apply**(*other*)

pandas.tseries.offsets.SemiMonthEnd.apply_index

SemiMonthEnd.**apply_index**(*other*)

pandas.tseries.offsets.SemiMonthEnd.copy

SemiMonthEnd.**copy**()

pandas.tseries.offsets.SemiMonthEnd.isAnchored

SemiMonthEnd.**isAnchored**()

pandas.tseries.offsets.SemiMonthEnd.onOffset

SemiMonthEnd.**onOffset**()

pandas.tseries.offsets.SemiMonthEnd.is_anchored

SemiMonthEnd.**is_anchored**()

pandas.tseries.offsets.SemiMonthEnd.is_on_offset

SemiMonthEnd.**is_on_offset**()

3.7.13 SemiMonthBegin

SemiMonthBegin	Two DateOffset's per month repeating on the first day of the month and day_of_month.

pandas.tseries.offsets.SemiMonthBegin

class pandas.tseries.offsets.**SemiMonthBegin**

Two DateOffset's per month repeating on the first day of the month and day_of_month.

Parameters

n [int]

normalize [bool, default False]

day_of_month [int, {2, 3,...,27}, default 15]

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.SemiMonthBegin.base

SemiMonthBegin.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

day_of_month	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.SemiMonthBegin.__call__

SemiMonthBegin.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.SemiMonthBegin.rollback

SemiMonthBegin.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.SemiMonthBegin.rollforward

SemiMonthBegin.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

SemiMonthBegin.freqstr
SemiMonthBegin.kwds
SemiMonthBegin.name
SemiMonthBegin.nanos
SemiMonthBegin.normalize
SemiMonthBegin.rule_code
SemiMonthBegin.n
SemiMonthBegin.day_of_month

pandas.tseries.offsets.SemiMonthBegin.freqstr

SemiMonthBegin.**freqstr**

pandas.tseries.offsets.SemiMonthBegin.kwds

SemiMonthBegin.**kwds**

pandas.tseries.offsets.SemiMonthBegin.name

SemiMonthBegin.**name**

pandas.tseries.offsets.SemiMonthBegin.nanos

SemiMonthBegin.**nanos**

pandas.tseries.offsets.SemiMonthBegin.normalize

SemiMonthBegin.**normalize**

pandas.tseries.offsets.SemiMonthBegin.rule_code

SemiMonthBegin.**rule_code**

pandas.tseries.offsets.SemiMonthBegin.n

SemiMonthBegin.**n**

pandas.tseries.offsets.SemiMonthBegin.day_of_month

SemiMonthBegin.**day_of_month**

Methods

SemiMonthBegin.apply(other)	
SemiMonthBegin.apply_index(other)	
SemiMonthBegin.copy	
SemiMonthBegin.isAnchored	
SemiMonthBegin.onOffset	
SemiMonthBegin.is_anchored	
SemiMonthBegin.is_on_offset	
SemiMonthBegin.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.SemiMonthBegin.apply

SemiMonthBegin.**apply**(*other*)

pandas.tseries.offsets.SemiMonthBegin.apply_index

SemiMonthBegin.**apply_index**(*other*)

pandas.tseries.offsets.SemiMonthBegin.copy

SemiMonthBegin.**copy**()

pandas.tseries.offsets.SemiMonthBegin.isAnchored

SemiMonthBegin.**isAnchored**()

pandas.tseries.offsets.SemiMonthBegin.onOffset

SemiMonthBegin.**onOffset**()

pandas.tseries.offsets.SemiMonthBegin.is_anchored

SemiMonthBegin.**is_anchored**()

pandas.tseries.offsets.SemiMonthBegin.is_on_offset

SemiMonthBegin.**is_on_offset**()

3.7.14 Week

Week	Weekly offset.

pandas.tseries.offsets.Week

class pandas.tseries.offsets.**Week**

Weekly offset.

Parameters

weekday [int or None, default None] Always generate specific day of week. 0 for Monday.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Week.base

Week.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
weekday	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Week.__call__

Week.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Week.rollback

Week.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Week.rollforward

Week.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Week.freqstr
Week.kwds
Week.name
Week.nanos
Week.normalize
Week.rule_code
Week.n
Week.weekday

pandas.tseries.offsets.Week.freqstr

Week.**freqstr**

pandas.tseries.offsets.Week.kwds

Week.**kwds**

pandas.tseries.offsets.Week.name

Week.**name**

pandas.tseries.offsets.Week.nanos

Week.**nanos**

pandas.tseries.offsets.Week.normalize

Week.**normalize**

pandas.tseries.offsets.Week.rule_code

Week.**rule_code**

pandas.tseries.offsets.Week.n

Week.**n**

pandas.tseries.offsets.Week.weekday

Week.**weekday**

Methods

Week.apply(other)	
Week.apply_index(other)	
Week.copy	
Week.isAnchored	
Week.onOffset	
Week.is_anchored	
Week.is_on_offset	
Week.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.Week.apply

Week.**apply**(*other*)

pandas.tseries.offsets.Week.apply_index

Week.**apply_index**(*other*)

pandas.tseries.offsets.Week.copy

Week.**copy**()

pandas.tseries.offsets.Week.isAnchored

Week.**isAnchored**()

pandas.tseries.offsets.Week.onOffset

Week.**onOffset**()

pandas.tseries.offsets.Week.is_anchored

Week.**is_anchored**()

pandas.tseries.offsets.Week.is_on_offset

Week.**is_on_offset**()

3.7.15 WeekOfMonth

WeekOfMonth	Describes monthly dates like "the Tuesday of the 2nd week of each month".

pandas.tseries.offsets.WeekOfMonth

class pandas.tseries.offsets.**WeekOfMonth**

Describes monthly dates like "the Tuesday of the 2nd week of each month".

Parameters

n [int]

week [int {0, 1, 2, 3, ...}, default 0] A specific integer for the week of the month. e.g. 0 is 1st week of month, 1 is the 2nd week, etc.

weekday [int {0, 1, ..., 6}, default 0] A specific integer for the day of the week.

- 0 is Monday

- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.WeekOfMonth.base

WeekOfMonth.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
week	
weekday	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.WeekOfMonth.__call__

WeekOfMonth.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.WeekOfMonth.rollback

WeekOfMonth.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.WeekOfMonth.rollforward

WeekOfMonth.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

WeekOfMonth.freqstr
WeekOfMonth.kwds
WeekOfMonth.name
WeekOfMonth.nanos
WeekOfMonth.normalize
WeekOfMonth.rule_code
WeekOfMonth.n
WeekOfMonth.week

pandas.tseries.offsets.WeekOfMonth.freqstr

WeekOfMonth.**freqstr**

pandas.tseries.offsets.WeekOfMonth.kwds

WeekOfMonth.**kwds**

pandas.tseries.offsets.WeekOfMonth.name

WeekOfMonth.**name**

pandas.tseries.offsets.WeekOfMonth.nanos

WeekOfMonth.**nanos**

pandas.tseries.offsets.WeekOfMonth.normalize

WeekOfMonth.**normalize**

pandas.tseries.offsets.WeekOfMonth.rule_code

WeekOfMonth.**rule_code**

pandas.tseries.offsets.WeekOfMonth.n

WeekOfMonth.**n**

pandas.tseries.offsets.WeekOfMonth.week

WeekOfMonth.**week**

Methods

WeekOfMonth.apply(other)	
WeekOfMonth.apply_index(other)	
WeekOfMonth.copy	
WeekOfMonth.isAnchored	
WeekOfMonth.onOffset	
WeekOfMonth.is_anchored	
WeekOfMonth.is_on_offset	
WeekOfMonth.__call__(*args, **kwargs)	Call self as a function.
WeekOfMonth.weekday	

pandas.tseries.offsets.WeekOfMonth.apply

WeekOfMonth.**apply**(*other*)

pandas.tseries.offsets.WeekOfMonth.apply_index

WeekOfMonth.**apply_index**(*other*)

pandas.tseries.offsets.WeekOfMonth.copy

WeekOfMonth.**copy**()

pandas.tseries.offsets.WeekOfMonth.isAnchored

WeekOfMonth.**isAnchored**()

pandas.tseries.offsets.WeekOfMonth.onOffset

WeekOfMonth.**onOffset**()

pandas.tseries.offsets.WeekOfMonth.is_anchored

WeekOfMonth.**is_anchored**()

pandas.tseries.offsets.WeekOfMonth.is_on_offset

WeekOfMonth.**is_on_offset**()

pandas.tseries.offsets.WeekOfMonth.weekday

WeekOfMonth.**weekday**

3.7.16 LastWeekOfMonth

LastWeekOfMonth	Describes monthly dates in last week of month like "the last Tuesday of each month".

pandas.tseries.offsets.LastWeekOfMonth

class pandas.tseries.offsets.**LastWeekOfMonth**

Describes monthly dates in last week of month like "the last Tuesday of each month".

Parameters

n [int, default 1]

weekday [int {0, 1, ..., 6}, default 0] A specific integer for the day of the week.

- 0 is Monday
- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.LastWeekOfMonth.base

LastWeekOfMonth.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
week	
weekday	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.LastWeekOfMonth.__call__

LastWeekOfMonth.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.LastWeekOfMonth.rollback

LastWeekOfMonth.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.LastWeekOfMonth.rollforward

LastWeekOfMonth.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

LastWeekOfMonth.freqstr
LastWeekOfMonth.kwds
LastWeekOfMonth.name
LastWeekOfMonth.nanos
LastWeekOfMonth.normalize
LastWeekOfMonth.rule_code
LastWeekOfMonth.n
LastWeekOfMonth.weekday
LastWeekOfMonth.week

pandas.tseries.offsets.LastWeekOfMonth.freqstr

LastWeekOfMonth.**freqstr**

pandas.tseries.offsets.LastWeekOfMonth.kwds

LastWeekOfMonth.**kwds**

pandas.tseries.offsets.LastWeekOfMonth.name

LastWeekOfMonth.**name**

pandas.tseries.offsets.LastWeekOfMonth.nanos

LastWeekOfMonth.**nanos**

pandas.tseries.offsets.LastWeekOfMonth.normalize

LastWeekOfMonth.**normalize**

pandas.tseries.offsets.LastWeekOfMonth.rule_code

LastWeekOfMonth.**rule_code**

pandas.tseries.offsets.LastWeekOfMonth.n

LastWeekOfMonth.**n**

pandas.tseries.offsets.LastWeekOfMonth.weekday

LastWeekOfMonth.**weekday**

pandas.tseries.offsets.LastWeekOfMonth.week

LastWeekOfMonth.**week**

Methods

LastWeekOfMonth.apply(other)	
LastWeekOfMonth.apply_index(other)	
LastWeekOfMonth.copy	
LastWeekOfMonth.isAnchored	
LastWeekOfMonth.onOffset	
LastWeekOfMonth.is_anchored	
LastWeekOfMonth.is_on_offset	
LastWeekOfMonth.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.LastWeekOfMonth.apply

LastWeekOfMonth.**apply**(*other*)

pandas.tseries.offsets.LastWeekOfMonth.apply_index

LastWeekOfMonth.**apply_index**(*other*)

pandas.tseries.offsets.LastWeekOfMonth.copy

LastWeekOfMonth.**copy**()

pandas.tseries.offsets.LastWeekOfMonth.isAnchored

LastWeekOfMonth.**isAnchored**()

pandas.tseries.offsets.LastWeekOfMonth.onOffset

LastWeekOfMonth.**onOffset**()

pandas.tseries.offsets.LastWeekOfMonth.is_anchored

LastWeekOfMonth.**is_anchored**()

pandas.tseries.offsets.LastWeekOfMonth.is_on_offset

LastWeekOfMonth.**is_on_offset**()

3.7.17 BQuarterEnd

BQuarterEnd	DateOffset increments between the last business day of each Quarter.

pandas.tseries.offsets.BQuarterEnd

class pandas.tseries.offsets.**BQuarterEnd**

DateOffset increments between the last business day of each Quarter.

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, ... startingMonth = 2 corresponds to dates like 2/28/2007, 5/31/2007, ... startingMonth = 3 corresponds to dates like 3/30/2007, 6/29/2007, ...

Examples

```
>>> from pandas.tseries.offset import BQuarterEnd
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BQuarterEnd()
Timestamp('2020-06-30 05:01:15')
>>> ts + BQuarterEnd(2)
Timestamp('2020-09-30 05:01:15')
>>> ts + BQuarterEnd(1, startingMonth=2)
Timestamp('2020-05-29 05:01:15')
>>> ts + BQuarterEnd(startingMonth=2)
Timestamp('2020-05-29 05:01:15')
```

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BQuarterEnd.base

BQuarterEnd.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
startingMonth	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BQuarterEnd.__call__

BQuarterEnd.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BQuarterEnd.rollback

BQuarterEnd.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BQuarterEnd.rollforward

BQuarterEnd.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

BQuarterEnd.freqstr
BQuarterEnd.kwds
BQuarterEnd.name
BQuarterEnd.nanos
BQuarterEnd.normalize
BQuarterEnd.rule_code
BQuarterEnd.n
BQuarterEnd.startingMonth

pandas.tseries.offsets.BQuarterEnd.freqstr

BQuarterEnd.**freqstr**

pandas.tseries.offsets.BQuarterEnd.kwds

BQuarterEnd.**kwds**

pandas.tseries.offsets.BQuarterEnd.name

BQuarterEnd.**name**

pandas.tseries.offsets.BQuarterEnd.nanos

BQuarterEnd.**nanos**

pandas.tseries.offsets.BQuarterEnd.normalize

BQuarterEnd.**normalize**

pandas.tseries.offsets.BQuarterEnd.rule_code

BQuarterEnd.**rule_code**

pandas.tseries.offsets.BQuarterEnd.n

BQuarterEnd.**n**

pandas.tseries.offsets.BQuarterEnd.startingMonth

BQuarterEnd.**startingMonth**

Methods

BQuarterEnd.apply(other)	
BQuarterEnd.apply_index(other)	
BQuarterEnd.copy	
BQuarterEnd.isAnchored	
BQuarterEnd.onOffset	
BQuarterEnd.is_anchored	
BQuarterEnd.is_on_offset	
BQuarterEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BQuarterEnd.apply

BQuarterEnd.**apply**(*other*)

pandas.tseries.offsets.BQuarterEnd.apply_index

BQuarterEnd.**apply_index**(*other*)

pandas.tseries.offsets.BQuarterEnd.copy

BQuarterEnd.**copy**()

pandas.tseries.offsets.BQuarterEnd.isAnchored

BQuarterEnd.**isAnchored**()

pandas.tseries.offsets.BQuarterEnd.onOffset

BQuarterEnd.**onOffset**()

pandas.tseries.offsets.BQuarterEnd.is_anchored

BQuarterEnd.**is_anchored**()

pandas.tseries.offsets.BQuarterEnd.is_on_offset

BQuarterEnd.**is_on_offset**()

3.7.18 BQuarterBegin

BQuarterBegin	DateOffset increments between the first business day of each Quarter.

pandas.tseries.offsets.BQuarterBegin

class pandas.tseries.offsets.**BQuarterBegin**

DateOffset increments between the first business day of each Quarter.

startingMonth = 1 corresponds to dates like 1/01/2007, 4/01/2007, … startingMonth = 2 corresponds to dates like 2/01/2007, 5/01/2007, … startingMonth = 3 corresponds to dates like 3/01/2007, 6/01/2007, …

Examples

```
>>> from pandas.tseries.offset import BQuarterBegin
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BQuarterBegin()
Timestamp('2020-06-01 05:01:15')
>>> ts + BQuarterBegin(2)
Timestamp('2020-09-01 05:01:15')
>>> ts + BQuarterBegin(startingMonth=2)
Timestamp('2020-08-03 05:01:15')
>>> ts + BQuarterBegin(-1)
Timestamp('2020-03-02 05:01:15')
```

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BQuarterBegin.base

BQuarterBegin.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
startingMonth	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BQuarterBegin.__call__

BQuarterBegin.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BQuarterBegin.rollback

BQuarterBegin.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BQuarterBegin.rollforward

BQuarterBegin.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

BQuarterBegin.freqstr
BQuarterBegin.kwds
BQuarterBegin.name
BQuarterBegin.nanos
BQuarterBegin.normalize
BQuarterBegin.rule_code
BQuarterBegin.n
BQuarterBegin.startingMonth

pandas.tseries.offsets.BQuarterBegin.freqstr

BQuarterBegin.**freqstr**

pandas.tseries.offsets.BQuarterBegin.kwds

BQuarterBegin.**kwds**

pandas.tseries.offsets.BQuarterBegin.name

BQuarterBegin.**name**

pandas.tseries.offsets.BQuarterBegin.nanos

BQuarterBegin.**nanos**

pandas.tseries.offsets.BQuarterBegin.normalize

BQuarterBegin.**normalize**

pandas.tseries.offsets.BQuarterBegin.rule_code

BQuarterBegin.**rule_code**

pandas.tseries.offsets.BQuarterBegin.n

BQuarterBegin.**n**

pandas.tseries.offsets.BQuarterBegin.startingMonth

BQuarterBegin.**startingMonth**

Methods

BQuarterBegin.apply(other)	
BQuarterBegin.apply_index(other)	
BQuarterBegin.copy	
BQuarterBegin.isAnchored	
BQuarterBegin.onOffset	
BQuarterBegin.is_anchored	
BQuarterBegin.is_on_offset	
BQuarterBegin.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BQuarterBegin.apply

BQuarterBegin.**apply**(*other*)

pandas.tseries.offsets.BQuarterBegin.apply_index

BQuarterBegin.**apply_index**(*other*)

pandas.tseries.offsets.BQuarterBegin.copy

BQuarterBegin.**copy**()

pandas.tseries.offsets.BQuarterBegin.isAnchored

BQuarterBegin.**isAnchored**()

pandas.tseries.offsets.BQuarterBegin.onOffset

BQuarterBegin.**onOffset**()

pandas.tseries.offsets.BQuarterBegin.is_anchored

BQuarterBegin.**is_anchored**()

pandas.tseries.offsets.BQuarterBegin.is_on_offset

BQuarterBegin.**is_on_offset**()

3.7.19 QuarterEnd

QuarterEnd	DateOffset increments between Quarter end dates.

pandas.tseries.offsets.QuarterEnd

class pandas.tseries.offsets.**QuarterEnd**

DateOffset increments between Quarter end dates.

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, … startingMonth = 2 corresponds to dates like 2/28/2007, 5/31/2007, … startingMonth = 3 corresponds to dates like 3/31/2007, 6/30/2007, …

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.QuarterEnd.base

QuarterEnd.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
startingMonth	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.QuarterEnd.__call__

QuarterEnd.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.QuarterEnd.rollback

QuarterEnd.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.QuarterEnd.rollforward

QuarterEnd.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

QuarterEnd.freqstr
QuarterEnd.kwds
QuarterEnd.name
QuarterEnd.nanos
QuarterEnd.normalize
QuarterEnd.rule_code
QuarterEnd.n
QuarterEnd.startingMonth

pandas.tseries.offsets.QuarterEnd.freqstr

QuarterEnd.**freqstr**

pandas.tseries.offsets.QuarterEnd.kwds

QuarterEnd.**kwds**

pandas.tseries.offsets.QuarterEnd.name

QuarterEnd.**name**

pandas.tseries.offsets.QuarterEnd.nanos

QuarterEnd.**nanos**

pandas.tseries.offsets.QuarterEnd.normalize

QuarterEnd.**normalize**

pandas.tseries.offsets.QuarterEnd.rule_code

QuarterEnd.**rule_code**

pandas.tseries.offsets.QuarterEnd.n

QuarterEnd.**n**

pandas.tseries.offsets.QuarterEnd.startingMonth

QuarterEnd.**startingMonth**

Methods

QuarterEnd.apply(other)	
QuarterEnd.apply_index(other)	
QuarterEnd.copy	
QuarterEnd.isAnchored	
QuarterEnd.onOffset	
QuarterEnd.is_anchored	
QuarterEnd.is_on_offset	
QuarterEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.QuarterEnd.apply

QuarterEnd.**apply**(*other*)

pandas.tseries.offsets.QuarterEnd.apply_index

QuarterEnd.**apply_index**(*other*)

pandas.tseries.offsets.QuarterEnd.copy

QuarterEnd.**copy**()

pandas.tseries.offsets.QuarterEnd.isAnchored

QuarterEnd.**isAnchored**()

pandas.tseries.offsets.QuarterEnd.onOffset

QuarterEnd.**onOffset**()

pandas.tseries.offsets.QuarterEnd.is_anchored

QuarterEnd.**is_anchored**()

pandas.tseries.offsets.QuarterEnd.is_on_offset

QuarterEnd.**is_on_offset**()

3.7.20 QuarterBegin

QuarterBegin	DateOffset increments between Quarter start dates.

pandas.tseries.offsets.QuarterBegin

class pandas.tseries.offsets.**QuarterBegin**

DateOffset increments between Quarter start dates.

startingMonth = 1 corresponds to dates like 1/01/2007, 4/01/2007, … startingMonth = 2 corresponds to dates like 2/01/2007, 5/01/2007, … startingMonth = 3 corresponds to dates like 3/01/2007, 6/01/2007, …

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.QuarterBegin.base

QuarterBegin.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
startingMonth	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.QuarterBegin.__call__

QuarterBegin.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.QuarterBegin.rollback

QuarterBegin.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.QuarterBegin.rollforward

QuarterBegin.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

QuarterBegin.freqstr
QuarterBegin.kwds
QuarterBegin.name
QuarterBegin.nanos
QuarterBegin.normalize
QuarterBegin.rule_code
QuarterBegin.n
QuarterBegin.startingMonth

pandas.tseries.offsets.QuarterBegin.freqstr

QuarterBegin.**freqstr**

pandas.tseries.offsets.QuarterBegin.kwds

QuarterBegin.**kwds**

pandas.tseries.offsets.QuarterBegin.name

QuarterBegin.**name**

pandas.tseries.offsets.QuarterBegin.nanos

QuarterBegin.**nanos**

pandas.tseries.offsets.QuarterBegin.normalize

QuarterBegin.**normalize**

pandas.tseries.offsets.QuarterBegin.rule_code

QuarterBegin.**rule_code**

pandas.tseries.offsets.QuarterBegin.n

QuarterBegin.**n**

pandas.tseries.offsets.QuarterBegin.startingMonth

QuarterBegin.**startingMonth**

Methods

QuarterBegin.apply(other)	
QuarterBegin.apply_index(other)	
QuarterBegin.copy	
QuarterBegin.isAnchored	
QuarterBegin.onOffset	
QuarterBegin.is_anchored	
QuarterBegin.is_on_offset	
QuarterBegin.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.QuarterBegin.apply

QuarterBegin.**apply**(*other*)

pandas.tseries.offsets.QuarterBegin.apply_index

QuarterBegin.**apply_index**(*other*)

pandas.tseries.offsets.QuarterBegin.copy

QuarterBegin.**copy**()

pandas.tseries.offsets.QuarterBegin.isAnchored

QuarterBegin.**isAnchored**()

pandas.tseries.offsets.QuarterBegin.onOffset

QuarterBegin.**onOffset**()

pandas.tseries.offsets.QuarterBegin.is_anchored

QuarterBegin.**is_anchored**()

pandas.tseries.offsets.QuarterBegin.is_on_offset

QuarterBegin.**is_on_offset**()

3.7.21 BYearEnd

BYearEnd	DateOffset increments between the last business day of the year.

pandas.tseries.offsets.BYearEnd

class pandas.tseries.offsets.**BYearEnd**

DateOffset increments between the last business day of the year.

Examples

```
>>> from pandas.tseries.offset import BYearEnd
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts - BYearEnd()
Timestamp('2019-12-31 05:01:15')
>>> ts + BYearEnd()
Timestamp('2020-12-31 05:01:15')
>>> ts + BYearEnd(3)
Timestamp('2022-12-30 05:01:15')
>>> ts + BYearEnd(-3)
Timestamp('2017-12-29 05:01:15')
>>> ts + BYearEnd(month=11)
Timestamp('2020-11-30 05:01:15')
```

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BYearEnd.base

BYearEnd.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
month	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BYearEnd.__call__

BYearEnd.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BYearEnd.rollback

BYearEnd.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BYearEnd.rollforward

BYearEnd.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

BYearEnd.freqstr
BYearEnd.kwds
BYearEnd.name
BYearEnd.nanos
BYearEnd.normalize
BYearEnd.rule_code
BYearEnd.n
BYearEnd.month

pandas.tseries.offsets.BYearEnd.freqstr

BYearEnd.**freqstr**

pandas.tseries.offsets.BYearEnd.kwds

BYearEnd.**kwds**

pandas.tseries.offsets.BYearEnd.name

BYearEnd.**name**

pandas.tseries.offsets.BYearEnd.nanos

BYearEnd.**nanos**

pandas.tseries.offsets.BYearEnd.normalize

BYearEnd.**normalize**

pandas.tseries.offsets.BYearEnd.rule_code

BYearEnd.**rule_code**

pandas.tseries.offsets.BYearEnd.n

BYearEnd.**n**

pandas.tseries.offsets.BYearEnd.month

BYearEnd.**month**

Methods

BYearEnd.apply(other)	
BYearEnd.apply_index(other)	
BYearEnd.copy	
BYearEnd.isAnchored	
BYearEnd.onOffset	
BYearEnd.is_anchored	
BYearEnd.is_on_offset	
BYearEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BYearEnd.apply

BYearEnd.**apply**(*other*)

pandas.tseries.offsets.BYearEnd.apply_index

BYearEnd.**apply_index**(*other*)

pandas.tseries.offsets.BYearEnd.copy

BYearEnd.**copy**()

pandas.tseries.offsets.BYearEnd.isAnchored

BYearEnd.**isAnchored**()

pandas.tseries.offsets.BYearEnd.onOffset

BYearEnd.**onOffset**()

pandas.tseries.offsets.BYearEnd.is_anchored

BYearEnd.**is_anchored**()

pandas.tseries.offsets.BYearEnd.is_on_offset

BYearEnd.**is_on_offset**()

3.7.22 BYearBegin

BYearBegin	DateOffset increments between the first business day of the year.

pandas.tseries.offsets.BYearBegin

class pandas.tseries.offsets.**BYearBegin**

DateOffset increments between the first business day of the year.

Examples

```
>>> from pandas.tseries.offset import BYearBegin
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BYearBegin()
Timestamp('2021-01-01 05:01:15')
>>> ts - BYearBegin()
Timestamp('2020-01-01 05:01:15')
>>> ts + BYearBegin(-1)
Timestamp('2020-01-01 05:01:15')
>>> ts + BYearBegin(2)
Timestamp('2022-01-03 05:01:15')
```

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BYearBegin.base

BYearBegin.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
month	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BYearBegin.__call__

BYearBegin.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.BYearBegin.rollback

BYearBegin.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BYearBegin.rollforward

BYearBegin.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

BYearBegin.freqstr
BYearBegin.kwds
BYearBegin.name
BYearBegin.nanos
BYearBegin.normalize
BYearBegin.rule_code
BYearBegin.n
BYearBegin.month

pandas.tseries.offsets.BYearBegin.freqstr

BYearBegin.**freqstr**

pandas.tseries.offsets.BYearBegin.kwds

BYearBegin.**kwds**

pandas.tseries.offsets.BYearBegin.name

BYearBegin.**name**

pandas.tseries.offsets.BYearBegin.nanos

BYearBegin.**nanos**

pandas.tseries.offsets.BYearBegin.normalize

BYearBegin.**normalize**

pandas.tseries.offsets.BYearBegin.rule_code

BYearBegin.**rule_code**

pandas.tseries.offsets.BYearBegin.n

BYearBegin.**n**

pandas.tseries.offsets.BYearBegin.month

BYearBegin.**month**

Methods

BYearBegin.apply(other)	
BYearBegin.apply_index(other)	
BYearBegin.copy	
BYearBegin.isAnchored	
BYearBegin.onOffset	
BYearBegin.is_anchored	
BYearBegin.is_on_offset	
BYearBegin.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.BYearBegin.apply

BYearBegin.**apply**(*other*)

pandas.tseries.offsets.BYearBegin.apply_index

BYearBegin.**apply_index**(*other*)

pandas.tseries.offsets.BYearBegin.copy

BYearBegin.**copy**()

pandas.tseries.offsets.BYearBegin.isAnchored

BYearBegin.**isAnchored**()

pandas.tseries.offsets.BYearBegin.onOffset

BYearBegin.**onOffset**()

pandas.tseries.offsets.BYearBegin.is_anchored

BYearBegin.**is_anchored**()

pandas.tseries.offsets.BYearBegin.is_on_offset

BYearBegin.**is_on_offset**()

3.7.23 YearEnd

YearEnd	DateOffset increments between calendar year ends.

pandas.tseries.offsets.YearEnd

class pandas.tseries.offsets.**YearEnd**

DateOffset increments between calendar year ends.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.YearEnd.base

YearEnd.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
month	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.YearEnd.__call__

YearEnd.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.YearEnd.rollback

YearEnd.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.YearEnd.rollforward

YearEnd.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

YearEnd.freqstr
YearEnd.kwds
YearEnd.name
YearEnd.nanos
YearEnd.normalize
YearEnd.rule_code
YearEnd.n
YearEnd.month

pandas.tseries.offsets.YearEnd.freqstr

YearEnd.**freqstr**

pandas.tseries.offsets.YearEnd.kwds

YearEnd.**kwds**

pandas.tseries.offsets.YearEnd.name

YearEnd.**name**

pandas.tseries.offsets.YearEnd.nanos

YearEnd.**nanos**

pandas.tseries.offsets.YearEnd.normalize

YearEnd.**normalize**

pandas.tseries.offsets.YearEnd.rule_code

YearEnd.**rule_code**

pandas.tseries.offsets.YearEnd.n

YearEnd.**n**

pandas.tseries.offsets.YearEnd.month

YearEnd.**month**

Methods

YearEnd.apply(other)	
YearEnd.apply_index(other)	
YearEnd.copy	
YearEnd.isAnchored	
YearEnd.onOffset	
YearEnd.is_anchored	
YearEnd.is_on_offset	
YearEnd.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.YearEnd.apply

YearEnd.**apply**(*other*)

pandas.tseries.offsets.YearEnd.apply_index

YearEnd.**apply_index**(*other*)

pandas.tseries.offsets.YearEnd.copy

YearEnd.**copy**()

pandas.tseries.offsets.YearEnd.isAnchored

YearEnd.**isAnchored**()

pandas.tseries.offsets.YearEnd.onOffset

YearEnd.**onOffset**()

pandas.tseries.offsets.YearEnd.is_anchored

YearEnd.**is_anchored**()

pandas.tseries.offsets.YearEnd.is_on_offset

YearEnd.**is_on_offset**()

3.7.24 YearBegin

YearBegin	DateOffset increments between calendar year begin dates.

pandas.tseries.offsets.YearBegin

class pandas.tseries.offsets.**YearBegin**

DateOffset increments between calendar year begin dates.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.YearBegin.base

YearBegin.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
month	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.YearBegin.__call__

YearBegin.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.YearBegin.rollback

YearBegin.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.YearBegin.rollforward

YearBegin.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

YearBegin.freqstr
YearBegin.kwds
YearBegin.name
YearBegin.nanos
YearBegin.normalize
YearBegin.rule_code
YearBegin.n
YearBegin.month

pandas.tseries.offsets.YearBegin.freqstr

YearBegin.**freqstr**

pandas.tseries.offsets.YearBegin.kwds

YearBegin.**kwds**

pandas.tseries.offsets.YearBegin.name

YearBegin.**name**

pandas.tseries.offsets.YearBegin.nanos

YearBegin.**nanos**

pandas.tseries.offsets.YearBegin.normalize

YearBegin.**normalize**

pandas.tseries.offsets.YearBegin.rule_code

YearBegin.**rule_code**

pandas.tseries.offsets.YearBegin.n

YearBegin.**n**

pandas.tseries.offsets.YearBegin.month

YearBegin.**month**

Methods

YearBegin.apply(other)	
YearBegin.apply_index(other)	
YearBegin.copy	
YearBegin.isAnchored	
YearBegin.onOffset	
YearBegin.is_anchored	
YearBegin.is_on_offset	
YearBegin.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.YearBegin.apply

YearBegin.**apply**(*other*)

pandas.tseries.offsets.YearBegin.apply_index

YearBegin.**apply_index**(*other*)

pandas.tseries.offsets.YearBegin.copy

YearBegin.**copy**()

pandas.tseries.offsets.YearBegin.isAnchored

YearBegin.**isAnchored**()

pandas.tseries.offsets.YearBegin.onOffset

YearBegin.**onOffset**()

pandas.tseries.offsets.YearBegin.is_anchored

YearBegin.**is_anchored**()

pandas.tseries.offsets.YearBegin.is_on_offset

YearBegin.**is_on_offset**()

3.7.25 FY5253

FY5253	Describes 52-53 week fiscal year.

pandas.tseries.offsets.FY5253

class pandas.tseries.offsets.**FY5253**

Describes 52-53 week fiscal year. This is also known as a 4-4-5 calendar.

It is used by companies that desire that their fiscal year always end on the same day of the week.

It is a method of managing accounting periods. It is a common calendar structure for some industries, such as retail, manufacturing and parking industry.

For more information see: https://en.wikipedia.org/wiki/4-4-5_calendar

The year may either:

- end on the last X day of the Y month.
- end on the last X day closest to the last day of the Y month.

X is a specific day of the week. Y is a certain month of the year

Parameters

n [int]

weekday [int {0, 1, . . . , 6}, default 0] A specific integer for the day of the week.

- 0 is Monday
- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

startingMonth [int {1, 2, . . . 12}, default 1] The month in which the fiscal year ends.

variation [str, default "nearest"] Method of employing 4-4-5 calendar.

There are two options:

- "nearest" means year end is **weekday** closest to last day of month in year.
- "last" means year end is final **weekday** of the final month in fiscal year.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.FY5253.base

FY5253.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	
startingMonth	
variation	
weekday	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.FY5253.__call__

FY5253.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.FY5253.rollback

FY5253.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.FY5253.rollforward

FY5253.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
get_rule_code_suffix	
get_year_end	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

FY5253.freqstr
FY5253.kwds
FY5253.name
FY5253.nanos
FY5253.normalize
FY5253.rule_code
FY5253.n
FY5253.startingMonth
FY5253.variation
FY5253.weekday

pandas.tseries.offsets.FY5253.freqstr

FY5253.**freqstr**

pandas.tseries.offsets.FY5253.kwds

FY5253.**kwds**

pandas.tseries.offsets.FY5253.name

FY5253.**name**

pandas.tseries.offsets.FY5253.nanos

FY5253.**nanos**

pandas.tseries.offsets.FY5253.normalize

FY5253.**normalize**

pandas.tseries.offsets.FY5253.rule_code

FY5253.**rule_code**

pandas.tseries.offsets.FY5253.n

FY5253.**n**

pandas.tseries.offsets.FY5253.startingMonth

FY5253.**startingMonth**

pandas.tseries.offsets.FY5253.variation

FY5253.**variation**

pandas.tseries.offsets.FY5253.weekday

FY5253.**weekday**

Methods

FY5253.apply(other)	
FY5253.apply_index(other)	
FY5253.copy	
FY5253.get_rule_code_suffix	
FY5253.get_year_end	
FY5253.isAnchored	
FY5253.onOffset	
FY5253.is_anchored	
FY5253.is_on_offset	
FY5253.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.FY5253.apply

FY5253.**apply**(*other*)

pandas.tseries.offsets.FY5253.apply_index

FY5253.**apply_index**(*other*)

pandas.tseries.offsets.FY5253.copy

FY5253.**copy**()

pandas.tseries.offsets.FY5253.get_rule_code_suffix

FY5253.**get_rule_code_suffix**()

pandas.tseries.offsets.FY5253.get_year_end

FY5253.**get_year_end**()

pandas.tseries.offsets.FY5253.isAnchored

FY5253.**isAnchored**()

pandas.tseries.offsets.FY5253.onOffset

FY5253.**onOffset**()

pandas.tseries.offsets.FY5253.is_anchored

FY5253.**is_anchored**()

pandas.tseries.offsets.FY5253.is_on_offset

FY5253.**is_on_offset**()

3.7.26 FY5253Quarter

FY5253Quarter	DateOffset increments between business quarter dates for 52-53 week fiscal year (also known as a 4-4-5 calendar).

pandas.tseries.offsets.FY5253Quarter

class pandas.tseries.offsets.**FY5253Quarter**

DateOffset increments between business quarter dates for 52-53 week fiscal year (also known as a 4-4-5 calendar).

It is used by companies that desire that their fiscal year always end on the same day of the week.

It is a method of managing accounting periods. It is a common calendar structure for some industries, such as retail, manufacturing and parking industry.

For more information see: https://en.wikipedia.org/wiki/4-4-5_calendar

The year may either:

- end on the last X day of the Y month.
- end on the last X day closest to the last day of the Y month.

X is a specific day of the week. Y is a certain month of the year

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, … startingMonth = 2 corresponds to dates like 2/28/2007, 5/31/2007, … startingMonth = 3 corresponds to dates like 3/30/2007, 6/29/2007, …

Parameters

n [int]

weekday [int {0, 1, …, 6}, default 0] A specific integer for the day of the week.

- 0 is Monday
- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

startingMonth [int {1, 2, …, 12}, default 1] The month in which fiscal years end.

qtr_with_extra_week [int {1, 2, 3, 4}, default 1] The quarter number that has the leap or 14 week when needed.

variation [str, default "nearest"] Method of employing 4-4-5 calendar.

There are two options:

- "nearest" means year end is **weekday** closest to last day of month in year.
- "last" means year end is final **weekday** of the final month in fiscal year.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.FY5253Quarter.base

FY5253Quarter.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
qtr_with_extra_week	
rule_code	
startingMonth	
variation	
weekday	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.FY5253Quarter.__call__

FY5253Quarter.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.FY5253Quarter.rollback

FY5253Quarter.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.FY5253Quarter.rollforward

FY5253Quarter.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
get_rule_code_suffix	
get_weeks	
isAnchored	
is_anchored	
is_on_offset	
onOffset	
year_has_extra_week	

Properties

FY5253Quarter.freqstr
FY5253Quarter.kwds
FY5253Quarter.name
FY5253Quarter.nanos
FY5253Quarter.normalize
FY5253Quarter.rule_code
FY5253Quarter.n
FY5253Quarter.qtr_with_extra_week
FY5253Quarter.startingMonth
FY5253Quarter.variation
FY5253Quarter.weekday

pandas.tseries.offsets.FY5253Quarter.freqstr

FY5253Quarter.**freqstr**

pandas.tseries.offsets.FY5253Quarter.kwds

FY5253Quarter.**kwds**

pandas.tseries.offsets.FY5253Quarter.name

FY5253Quarter.**name**

pandas.tseries.offsets.FY5253Quarter.nanos

FY5253Quarter.**nanos**

pandas.tseries.offsets.FY5253Quarter.normalize

FY5253Quarter.**normalize**

pandas.tseries.offsets.FY5253Quarter.rule_code

FY5253Quarter.**rule_code**

pandas.tseries.offsets.FY5253Quarter.n

FY5253Quarter.**n**

pandas.tseries.offsets.FY5253Quarter.qtr_with_extra_week

FY5253Quarter.**qtr_with_extra_week**

pandas.tseries.offsets.FY5253Quarter.startingMonth

FY5253Quarter.**startingMonth**

pandas.tseries.offsets.FY5253Quarter.variation

FY5253Quarter.**variation**

pandas.tseries.offsets.FY5253Quarter.weekday

FY5253Quarter.**weekday**

Methods

FY5253Quarter.apply(other)	
FY5253Quarter.apply_index(other)	
FY5253Quarter.copy	
FY5253Quarter.get_rule_code_suffix	
FY5253Quarter.get_weeks	
FY5253Quarter.isAnchored	
FY5253Quarter.onOffset	
FY5253Quarter.is_anchored	
FY5253Quarter.is_on_offset	
FY5253Quarter.year_has_extra_week	
FY5253Quarter.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.FY5253Quarter.apply

FY5253Quarter.**apply**(*other*)

pandas.tseries.offsets.FY5253Quarter.apply_index

FY5253Quarter.**apply_index**(*other*)

pandas.tseries.offsets.FY5253Quarter.copy

FY5253Quarter.**copy**()

pandas.tseries.offsets.FY5253Quarter.get_rule_code_suffix

FY5253Quarter.**get_rule_code_suffix**()

pandas.tseries.offsets.FY5253Quarter.get_weeks

FY5253Quarter.**get_weeks**()

pandas.tseries.offsets.FY5253Quarter.isAnchored

FY5253Quarter.**isAnchored**()

pandas.tseries.offsets.FY5253Quarter.onOffset

FY5253Quarter.**onOffset**()

pandas.tseries.offsets.FY5253Quarter.is_anchored

FY5253Quarter.**is_anchored**()

pandas.tseries.offsets.FY5253Quarter.is_on_offset

FY5253Quarter.**is_on_offset**()

pandas.tseries.offsets.FY5253Quarter.year_has_extra_week

FY5253Quarter.**year_has_extra_week**()

3.7.27 Easter

Easter	DateOffset for the Easter holiday using logic defined in dateutil.

pandas.tseries.offsets.Easter

class pandas.tseries.offsets.**Easter**

DateOffset for the Easter holiday using logic defined in dateutil.

Right now uses the revised method which is valid in years 1583-4099.

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Easter.base

Easter.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Easter.__call__

Easter.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Easter.rollback

Easter.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Easter.rollforward

Easter.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Easter.freqstr
Easter.kwds
Easter.name
Easter.nanos
Easter.normalize
Easter.rule_code
Easter.n

pandas.tseries.offsets.Easter.freqstr

Easter.**freqstr**

pandas.tseries.offsets.Easter.kwds

Easter.**kwds**

pandas.tseries.offsets.Easter.name

Easter.**name**

pandas.tseries.offsets.Easter.nanos

Easter.**nanos**

pandas.tseries.offsets.Easter.normalize

Easter.**normalize**

pandas.tseries.offsets.Easter.rule_code

Easter.**rule_code**

pandas.tseries.offsets.Easter.n

Easter.**n**

Methods

Easter.apply(other)	
Easter.apply_index(other)	
Easter.copy	
Easter.isAnchored	
Easter.onOffset	
Easter.is_anchored	
Easter.is_on_offset	
Easter.__call__(*args, **kwargs)	Call self as a function.

pandas.tseries.offsets.Easter.apply

Easter.**apply**(*other*)

pandas.tseries.offsets.Easter.apply_index

Easter.**apply_index**(*other*)

pandas.tseries.offsets.Easter.copy

Easter.**copy**()

pandas.tseries.offsets.Easter.isAnchored

Easter.**isAnchored**()

pandas.tseries.offsets.Easter.onOffset

Easter.**onOffset**()

pandas.tseries.offsets.Easter.is_anchored

Easter.**is_anchored**()

pandas.tseries.offsets.Easter.is_on_offset

Easter.**is_on_offset**()

3.7.28 Tick

Tick

Attributes

pandas.tseries.offsets.Tick

class pandas.tseries.offsets.**Tick**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Tick.base

Tick.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Tick.__call__

Tick.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Tick.rollback

Tick.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Tick.rollforward

Tick.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Tick.delta
Tick.freqstr
Tick.kwds
Tick.name
Tick.nanos
Tick.normalize
Tick.rule_code
Tick.n

pandas.tseries.offsets.Tick.delta

Tick.**delta**

pandas.tseries.offsets.Tick.freqstr

Tick.**freqstr**

pandas.tseries.offsets.Tick.kwds

Tick.**kwds**

pandas.tseries.offsets.Tick.name

Tick.**name**

pandas.tseries.offsets.Tick.nanos

Tick.**nanos**

pandas.tseries.offsets.Tick.normalize

Tick.**normalize**

pandas.tseries.offsets.Tick.rule_code

Tick.**rule_code**

pandas.tseries.offsets.Tick.n

Tick.**n**

Methods

Tick.copy	
Tick.isAnchored	
Tick.onOffset	
Tick.is_anchored	
Tick.is_on_offset	
Tick.__call__(*args, **kwargs)	Call self as a function.
Tick.apply	
Tick.apply_index(other)	

pandas.tseries.offsets.Tick.copy

Tick.**copy**()

pandas.tseries.offsets.Tick.isAnchored

Tick.**isAnchored**()

pandas.tseries.offsets.Tick.onOffset

Tick.**onOffset**()

pandas.tseries.offsets.Tick.is_anchored

Tick.**is_anchored**()

pandas.tseries.offsets.Tick.is_on_offset

Tick.**is_on_offset**()

pandas.tseries.offsets.Tick.apply

Tick.**apply**()

pandas.tseries.offsets.Tick.apply_index

Tick.**apply_index**(*other*)

3.7.29 Day

Day

Attributes

pandas.tseries.offsets.Day

class pandas.tseries.offsets.**Day**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Day.base

Day.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Day.__call__

Day.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Day.rollback

Day.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Day.rollforward

Day.**rollforward**()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Day.delta
Day.freqstr
Day.kwds
Day.name
Day.nanos
Day.normalize
Day.rule_code
Day.n

pandas.tseries.offsets.Day.delta

Day.**delta**

pandas.tseries.offsets.Day.freqstr

Day.**freqstr**

pandas.tseries.offsets.Day.kwds

Day.**kwds**

pandas.tseries.offsets.Day.name

Day.**name**

pandas.tseries.offsets.Day.nanos

Day.**nanos**

pandas.tseries.offsets.Day.normalize

Day.**normalize**

pandas.tseries.offsets.Day.rule_code

Day.**rule_code**

pandas.tseries.offsets.Day.n

Day.**n**

Methods

Day.copy	
Day.isAnchored	
Day.onOffset	
Day.is_anchored	
Day.is_on_offset	
Day.__call__(*args, **kwargs)	Call self as a function.
Day.apply	
Day.apply_index(other)	

pandas.tseries.offsets.Day.copy

Day.**copy**()

pandas.tseries.offsets.Day.isAnchored

Day.**isAnchored**()

pandas.tseries.offsets.Day.onOffset

Day.**onOffset**()

pandas.tseries.offsets.Day.is_anchored

Day.**is_anchored**()

pandas.tseries.offsets.Day.is_on_offset

Day.**is_on_offset**()

pandas.tseries.offsets.Day.apply

Day.**apply**()

pandas.tseries.offsets.Day.apply_index

Day.**apply_index**(*other*)

3.7.30 Hour

Hour

Attributes

pandas.tseries.offsets.Hour

class pandas.tseries.offsets.**Hour**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Hour.base

Hour.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Hour.__call__

Hour.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Hour.rollback

Hour.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Hour.rollforward

Hour.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Hour.delta
Hour.freqstr
Hour.kwds
Hour.name
Hour.nanos
Hour.normalize
Hour.rule_code
Hour.n

pandas.tseries.offsets.Hour.delta

Hour.**delta**

pandas.tseries.offsets.Hour.freqstr

Hour.**freqstr**

pandas.tseries.offsets.Hour.kwds

Hour.**kwds**

pandas.tseries.offsets.Hour.name

Hour.**name**

pandas.tseries.offsets.Hour.nanos

Hour.**nanos**

pandas.tseries.offsets.Hour.normalize

Hour.**normalize**

pandas.tseries.offsets.Hour.rule_code

Hour.**rule_code**

pandas.tseries.offsets.Hour.n

Hour.**n**

Methods

Hour.copy	
Hour.isAnchored	
Hour.onOffset	
Hour.is_anchored	
Hour.is_on_offset	
Hour.__call__(*args, **kwargs)	Call self as a function.
Hour.apply	
Hour.apply_index(other)	

pandas.tseries.offsets.Hour.copy

Hour.**copy**()

pandas.tseries.offsets.Hour.isAnchored

Hour.**isAnchored**()

pandas.tseries.offsets.Hour.onOffset

Hour.**onOffset**()

pandas.tseries.offsets.Hour.is_anchored

Hour.**is_anchored**()

pandas.tseries.offsets.Hour.is_on_offset

Hour.**is_on_offset**()

pandas.tseries.offsets.Hour.apply

Hour.**apply**()

pandas.tseries.offsets.Hour.apply_index

Hour.**apply_index**(*other*)

3.7.31 Minute

Minute

Attributes

pandas.tseries.offsets.Minute

class pandas.tseries.offsets.**Minute**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Minute.base

Minute.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Minute.__call__

Minute.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Minute.rollback

Minute.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Minute.rollforward

Minute.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Minute.delta
Minute.freqstr
Minute.kwds
Minute.name
Minute.nanos
Minute.normalize
Minute.rule_code
Minute.n

pandas.tseries.offsets.Minute.delta

Minute.**delta**

pandas.tseries.offsets.Minute.freqstr

Minute.**freqstr**

pandas.tseries.offsets.Minute.kwds

Minute.**kwds**

pandas.tseries.offsets.Minute.name

Minute.**name**

pandas.tseries.offsets.Minute.nanos

Minute.**nanos**

pandas.tseries.offsets.Minute.normalize

Minute.**normalize**

pandas.tseries.offsets.Minute.rule_code

Minute.**rule_code**

pandas.tseries.offsets.Minute.n

Minute.**n**

Methods

Minute.copy	
Minute.isAnchored	
Minute.onOffset	
Minute.is_anchored	
Minute.is_on_offset	
Minute.__call__(*args, **kwargs)	Call self as a function.
Minute.apply	
Minute.apply_index(other)	

pandas.tseries.offsets.Minute.copy

Minute.**copy**()

pandas.tseries.offsets.Minute.isAnchored

Minute.**isAnchored**()

pandas.tseries.offsets.Minute.onOffset

Minute.**onOffset**()

pandas.tseries.offsets.Minute.is_anchored

Minute.**is_anchored**()

pandas.tseries.offsets.Minute.is_on_offset

Minute.**is_on_offset**()

pandas.tseries.offsets.Minute.apply

Minute.**apply**()

pandas.tseries.offsets.Minute.apply_index

Minute.**apply_index**(*other*)

3.7.32 Second

Second

Attributes

pandas.tseries.offsets.Second

class pandas.tseries.offsets.**Second**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Second.base

Second.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Second.__call__

Second.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Second.rollback

Second.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Second.rollforward

Second.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Second.delta
Second.freqstr
Second.kwds
Second.name
Second.nanos
Second.normalize
Second.rule_code
Second.n

pandas.tseries.offsets.Second.delta

Second.**delta**

pandas.tseries.offsets.Second.freqstr

Second.**freqstr**

pandas.tseries.offsets.Second.kwds

Second.**kwds**

pandas.tseries.offsets.Second.name

Second.**name**

pandas.tseries.offsets.Second.nanos

Second.**nanos**

pandas.tseries.offsets.Second.normalize

Second.**normalize**

pandas.tseries.offsets.Second.rule_code

Second.**rule_code**

pandas.tseries.offsets.Second.n

Second.**n**

Methods

Second.copy	
Second.isAnchored	
Second.onOffset	
Second.is_anchored	
Second.is_on_offset	
Second.__call__(*args, **kwargs)	Call self as a function.
Second.apply	
Second.apply_index(other)	

pandas.tseries.offsets.Second.copy

Second.**copy**()

pandas.tseries.offsets.Second.isAnchored

Second.**isAnchored**()

pandas.tseries.offsets.Second.onOffset

Second.**onOffset**()

pandas.tseries.offsets.Second.is_anchored

Second.**is_anchored**()

pandas.tseries.offsets.Second.is_on_offset

Second.**is_on_offset**()

pandas.tseries.offsets.Second.apply

Second.**apply**()

pandas.tseries.offsets.Second.apply_index

Second.**apply_index**(*other*)

3.7.33 Milli

Milli

Attributes

pandas.tseries.offsets.Milli

class pandas.tseries.offsets.**Milli**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Milli.base

Milli.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Milli.__call__

Milli.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Milli.rollback

Milli.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Milli.rollforward

Milli.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Milli.delta
Milli.freqstr
Milli.kwds
Milli.name
Milli.nanos
Milli.normalize
Milli.rule_code
Milli.n

pandas.tseries.offsets.Milli.delta

Milli.**delta**

pandas.tseries.offsets.Milli.freqstr

Milli.**freqstr**

pandas.tseries.offsets.Milli.kwds

Milli.**kwds**

pandas.tseries.offsets.Milli.name

Milli.**name**

pandas.tseries.offsets.Milli.nanos

Milli.**nanos**

pandas.tseries.offsets.Milli.normalize

Milli.**normalize**

pandas.tseries.offsets.Milli.rule_code

Milli.**rule_code**

pandas.tseries.offsets.Milli.n

Milli.**n**

Methods

Milli.copy	
Milli.isAnchored	
Milli.onOffset	
Milli.is_anchored	
Milli.is_on_offset	
Milli.__call__(*args, **kwargs)	Call self as a function.
Milli.apply	
Milli.apply_index(other)	

pandas.tseries.offsets.Milli.copy

Milli.**copy**()

pandas.tseries.offsets.Milli.isAnchored

Milli.**isAnchored**()

pandas.tseries.offsets.Milli.onOffset

Milli.**onOffset**()

pandas.tseries.offsets.Milli.is_anchored

Milli.**is_anchored**()

pandas.tseries.offsets.Milli.is_on_offset

Milli.**is_on_offset**()

pandas.tseries.offsets.Milli.apply

Milli.**apply**()

pandas.tseries.offsets.Milli.apply_index

Milli.**apply_index**(*other*)

3.7.34 Micro

Micro

Attributes

pandas.tseries.offsets.Micro

class pandas.tseries.offsets.**Micro**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Micro.base

Micro.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Micro.__call__

Micro.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Micro.rollback

Micro.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Micro.rollforward

Micro.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Micro.delta
Micro.freqstr
Micro.kwds
Micro.name
Micro.nanos
Micro.normalize
Micro.rule_code
Micro.n

pandas.tseries.offsets.Micro.delta

Micro.**delta**

pandas.tseries.offsets.Micro.freqstr

Micro.**freqstr**

pandas.tseries.offsets.Micro.kwds

Micro.**kwds**

pandas.tseries.offsets.Micro.name

Micro.**name**

pandas.tseries.offsets.Micro.nanos

Micro.**nanos**

pandas.tseries.offsets.Micro.normalize

Micro.**normalize**

pandas.tseries.offsets.Micro.rule_code

Micro.**rule_code**

pandas.tseries.offsets.Micro.n

Micro.**n**

Methods

Micro.copy	
Micro.isAnchored	
Micro.onOffset	
Micro.is_anchored	
Micro.is_on_offset	
Micro.__call__(*args, **kwargs)	Call self as a function.
Micro.apply	
Micro.apply_index(other)	

pandas.tseries.offsets.Micro.copy

Micro.**copy**()

pandas.tseries.offsets.Micro.isAnchored

Micro.**isAnchored**()

pandas.tseries.offsets.Micro.onOffset

Micro.**onOffset**()

pandas.tseries.offsets.Micro.is_anchored

Micro.**is_anchored**()

pandas.tseries.offsets.Micro.is_on_offset

Micro.**is_on_offset**()

pandas.tseries.offsets.Micro.apply

Micro.**apply**()

pandas.tseries.offsets.Micro.apply_index

Micro.**apply_index**(*other*)

3.7.35 Nano

Nano

Attributes

pandas.tseries.offsets.Nano

class pandas.tseries.offsets.**Nano**

Attributes

base	Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.Nano.base

Nano.**base**
Returns a copy of the calling offset object with n=1 and all other attributes equal.

delta	
freqstr	
kwds	
n	
name	
nanos	
normalize	
rule_code	

Methods

__call__(*args, **kwargs)	Call self as a function.
rollback	Roll provided date backward to next offset only if not on offset.
rollforward	Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Nano.__call__

Nano.**__call__**(**args*, ***kwargs*)
Call self as a function.

pandas.tseries.offsets.Nano.rollback

Nano.**rollback**()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Nano.rollforward

Nano.**rollforward**()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply	
apply_index	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

Properties

Nano.delta
Nano.freqstr
Nano.kwds
Nano.name
Nano.nanos
Nano.normalize
Nano.rule_code
Nano.n

pandas.tseries.offsets.Nano.delta

Nano.**delta**

pandas.tseries.offsets.Nano.freqstr

Nano.**freqstr**

pandas.tseries.offsets.Nano.kwds

Nano.**kwds**

pandas.tseries.offsets.Nano.name

Nano.**name**

pandas.tseries.offsets.Nano.nanos

Nano.**nanos**

pandas.tseries.offsets.Nano.normalize

Nano.**normalize**

pandas.tseries.offsets.Nano.rule_code

Nano.**rule_code**

pandas.tseries.offsets.Nano.n

Nano.**n**

Methods

Nano.copy	
Nano.isAnchored	
Nano.onOffset	
Nano.is_anchored	
Nano.is_on_offset	
Nano.__call__(*args, **kwargs)	Call self as a function.
Nano.apply	
Nano.apply_index(other)	

pandas.tseries.offsets.Nano.copy

Nano.**copy**()

pandas.tseries.offsets.Nano.isAnchored

Nano.**isAnchored**()

pandas.tseries.offsets.Nano.onOffset

Nano.**onOffset**()

pandas.tseries.offsets.Nano.is_anchored

Nano.**is_anchored**()

pandas.tseries.offsets.Nano.is_on_offset

Nano.**is_on_offset**()

pandas.tseries.offsets.Nano.apply

Nano.**apply**()

pandas.tseries.offsets.Nano.apply_index

Nano.**apply_index**(*other*)

3.8 Frequencies

to_offset	Return DateOffset object from string or tuple representation or datetime.timedelta object.

3.8.1 pandas.tseries.frequencies.to_offset

pandas.tseries.frequencies.**to_offset**()

Return DateOffset object from string or tuple representation or datetime.timedelta object.

Parameters

freq [str, tuple, datetime.timedelta, DateOffset or None]

Returns

DateOffset or None

Raises

ValueError If freq is an invalid frequency

See also:

DateOffset Standard kind of date increment used for a date range.

Examples

```
>>> to_offset("5min")
<5 * Minutes>
```

```
>>> to_offset("1D1H")
<25 * Hours>
```

```
>>> to_offset("2W")
<2 * Weeks: weekday=6>
```

```
>>> to_offset("2B")
<2 * BusinessDays>
```

```
>>> to_offset(pd.Timedelta(days=1))
<Day>
```

```
>>> to_offset(Hour())
<Hour>
```

3.9 Window

Rolling objects are returned by `.rolling` calls: *pandas.DataFrame.rolling()*, *pandas.Series.rolling()*, etc. Expanding objects are returned by `.expanding` calls: *pandas.DataFrame.expanding()*, *pandas.Series.expanding()*, etc. ExponentialMovingWindow objects are returned by `.ewm` calls: *pandas.DataFrame.ewm()*, *pandas.Series.ewm()*, etc.

3.9.1 Rolling window functions

Rolling.count()	The rolling count of any non-NaN observations inside the window.
Rolling.sum(*args, **kwargs)	Calculate rolling sum of given DataFrame or Series.
Rolling.mean(*args, **kwargs)	Calculate the rolling mean of the values.
Rolling.median(**kwargs)	Calculate the rolling median.
Rolling.var([ddof])	Calculate unbiased rolling variance.
Rolling.std([ddof])	Calculate rolling standard deviation.
Rolling.min(*args, **kwargs)	Calculate the rolling minimum.
Rolling.max(*args, **kwargs)	Calculate the rolling maximum.
Rolling.corr([other, pairwise])	Calculate rolling correlation.
Rolling.cov([other, pairwise, ddof])	Calculate the rolling sample covariance.
Rolling.skew(**kwargs)	Unbiased rolling skewness.
Rolling.kurt(**kwargs)	Calculate unbiased rolling kurtosis.
Rolling.apply(func[, raw, engine, ...])	Apply an arbitrary function to each rolling window.

continues on next page

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Rolling.aggregate(func, *args, **kwargs)	Aggregate using one or more operations over the specified axis.
Rolling.quantile(quantile[, interpolation])	Calculate the rolling quantile.
Rolling.sem([ddof])	Compute rolling standard error of mean.

pandas.core.window.rolling.Rolling.count

Rolling.**count**()

The rolling count of any non-NaN observations inside the window.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.DataFrame.count Count of the full DataFrame.

Examples

```
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0    1.0
1    2.0
2    1.0
3    1.0
dtype: float64
>>> s.rolling(3).count()
0    1.0
1    2.0
2    2.0
3    2.0
dtype: float64
>>> s.rolling(4).count()
0    1.0
1    2.0
2    2.0
3    3.0
dtype: float64
```

pandas.core.window.rolling.Rolling.sum

Rolling.**sum**(**args*, ***kwargs*)

Calculate rolling sum of given DataFrame or Series.

Parameters

***args, **kwargs** For compatibility with other rolling methods. Has no effect on the computed value.

Returns

Series or DataFrame Same type as the input, with the same index, containing the rolling sum.

See also:

pandas.Series.sum Reducing sum for Series.
pandas.DataFrame.sum Reducing sum for DataFrame.

Examples

```
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

```
>>> s.rolling(3).sum()
0     NaN
1     NaN
2     6.0
3     9.0
4    12.0
dtype: float64
```

```
>>> s.expanding(3).sum()
0     NaN
1     NaN
2     6.0
3    10.0
4    15.0
dtype: float64
```

```
>>> s.rolling(3, center=True).sum()
0     NaN
1     6.0
2     9.0
3    12.0
4     NaN
dtype: float64
```

For DataFrame, each rolling sum is computed column-wise.

```
>>> df = pd.DataFrame({"A": s, "B": s ** 2})
>>> df
   A   B
0  1   1
1  2   4
2  3   9
3  4  16
4  5  25
```

```
>>> df.rolling(3).sum()
      A     B
0   NaN   NaN
1   NaN   NaN
```

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```
2   6.0  14.0
3   9.0  29.0
4  12.0  50.0
```

pandas.core.window.rolling.Rolling.mean

Rolling.**mean**(**args*, ***kwargs*)

Calculate the rolling mean of the values.

Parameters

***args** Under Review.

****kwargs** Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.mean Equivalent method for Series.
pandas.DataFrame.mean Equivalent method for DataFrame.

Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64
```

```
>>> s.rolling(3).mean()
0    NaN
1    NaN
2    2.0
3    3.0
dtype: float64
```

pandas.core.window.rolling.Rolling.median

Rolling.**median**(***kwargs*)

Calculate the rolling median.

Parameters

****kwargs** For compatibility with other rolling methods. Has no effect on the computed median.

Returns

Series or DataFrame Returned type is the same as the original object.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.median Equivalent method for Series.
pandas.DataFrame.median Equivalent method for DataFrame.

Examples

Compute the rolling median of a series with a window size of 3.

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0    NaN
1    NaN
2    1.0
3    2.0
4    3.0
dtype: float64
```

pandas.core.window.rolling.Rolling.var

Rolling.**var**(*ddof=1*, **args*, ***kwargs*)

Calculate unbiased rolling variance.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.var Equivalent method for Series.
pandas.DataFrame.var Equivalent method for DataFrame.
numpy.var Equivalent method for Numpy array.

Notes

The default *ddof* of 1 used in `Series.var()` is different than the default *ddof* of 0 in `numpy.var()`.

A minimum of 1 period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0         NaN
1         NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).var()
0         NaN
1         NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

pandas.core.window.rolling.Rolling.std

`Rolling.`**`std`**(*ddof=1*, **args*, ***kwargs*)

Calculate rolling standard deviation.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the rolling calculation.

See also:

`pandas.Series.rolling` Calling object with Series data.
`pandas.DataFrame.rolling` Calling object with DataFrames.
`pandas.Series.std` Equivalent method for Series.
`pandas.DataFrame.std` Equivalent method for DataFrame.
`numpy.std` Equivalent method for Numpy array.

Notes

The default *ddof* of 1 used in Series.std is different than the default *ddof* of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0         NaN
1         NaN
2    0.577350
3    1.000000
4    1.000000
5    1.154701
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).std()
0         NaN
1         NaN
2    0.577350
3    0.957427
4    0.894427
5    0.836660
6    0.786796
dtype: float64
```

pandas.core.window.rolling.Rolling.min

Rolling.**min**(**args*, ***kwargs*)

Calculate the rolling minimum.

Parameters

****kwargs** Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with a Series.
pandas.DataFrame.rolling Calling object with a DataFrame.
pandas.Series.min Similar method for Series.
pandas.DataFrame.min Similar method for DataFrame.

Examples

Performing a rolling minimum with a window size of 3.

```
>>> s = pd.Series([4, 3, 5, 2, 6])
>>> s.rolling(3).min()
0    NaN
1    NaN
2    3.0
3    2.0
4    2.0
dtype: float64
```

pandas.core.window.rolling.Rolling.max

Rolling.**max**(**args*, ***kwargs*)

Calculate the rolling maximum.

Parameters

***args, **kwargs** Arguments and keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrame data.
pandas.Series.max Similar method for Series.
pandas.DataFrame.max Similar method for DataFrame.

pandas.core.window.rolling.Rolling.corr

Rolling.**corr**(*other=None*, *pairwise=None*, ***kwargs*)

Calculate rolling correlation.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self.

pairwise [bool, default None] Calculate pairwise combinations of columns within a DataFrame. If *other* is not specified, defaults to *True*, otherwise defaults to *False*. Not relevant for *Series*.

****kwargs** Unused.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.corr Equivalent method for Series.
pandas.DataFrame.corr Equivalent method for DataFrame.
cov Similar method to calculate covariance.
numpy.corrcoef NumPy Pearson's correlation calculation.

Notes

This function uses Pearson's definition of correlation (https://en.wikipedia.org/wiki/Pearson_correlation_coefficient).

When *other* is not specified, the output will be self correlation (e.g. all 1's), except for *DataFrame* inputs with *pairwise* set to *True*.

Function will return `NaN` for correlations of equal valued sequences; this is the result of a 0/0 division error.

When *pairwise* is set to *False*, only matching columns between *self* and *other* will be used.

When *pairwise* is set to *True*, the output will be a MultiIndex DataFrame with the original index on the first level, and the *other* DataFrame columns on the second level.

In the case of missing elements, only complete pairwise observations will be used.

Examples

The below example shows a rolling calculation with a window size of four matching the equivalent function call using `numpy.corrcoef()`.

```
>>> v1 = [3, 3, 3, 5, 8]
>>> v2 = [3, 4, 4, 4, 8]
>>> # numpy returns a 2X2 array, the correlation coefficient
>>> # is the number at entry [0][1]
>>> print(f"{np.corrcoef(v1[:-1], v2[:-1])[0][1]:.6f}")
0.333333
>>> print(f"{np.corrcoef(v1[1:], v2[1:])[0][1]:.6f}")
0.916949
>>> s1 = pd.Series(v1)
>>> s2 = pd.Series(v2)
>>> s1.rolling(4).corr(s2)
0         NaN
1         NaN
2         NaN
3    0.333333
4    0.916949
dtype: float64
```

The below example shows a similar rolling calculation on a DataFrame using the pairwise option.

```
>>> matrix = np.array([[51., 35.], [49., 30.], [47., 32.],    [46., 31.], [50.,␣
↪36.]])
>>> print(np.corrcoef(matrix[:-1,0], matrix[:-1,1]).round(7))
[[1.         0.6263001]
 [0.6263001  1.       ]]
>>> print(np.corrcoef(matrix[1:,0], matrix[1:,1]).round(7))
[[1.         0.5553681]
 [0.5553681  1.       ]]
>>> df = pd.DataFrame(matrix, columns=['X','Y'])
>>> df
      X     Y
0  51.0  35.0
1  49.0  30.0
2  47.0  32.0
3  46.0  31.0
4  50.0  36.0
```

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```
>>> df.rolling(4).corr(pairwise=True)
              X         Y
0 X       NaN       NaN
  Y       NaN       NaN
1 X       NaN       NaN
  Y       NaN       NaN
2 X       NaN       NaN
  Y       NaN       NaN
3 X  1.000000  0.626300
  Y  0.626300  1.000000
4 X  1.000000  0.555368
  Y  0.555368  1.000000
```

pandas.core.window.rolling.Rolling.cov

`Rolling.`**`cov`**(*other=None*, *pairwise=None*, *ddof=1*, ***kwargs*)

Calculate the rolling sample covariance.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

pairwise [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndexed DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

****kwargs** Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrame data.
pandas.Series.cov Similar method for Series.
pandas.DataFrame.cov Similar method for DataFrame.

pandas.core.window.rolling.Rolling.skew

`Rolling.`**`skew`**(***kwargs*)

Unbiased rolling skewness.

Parameters

****kwargs** Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.rolling Calling object with Series data.

pandas.DataFrame.rolling Calling object with DataFrame data.
pandas.Series.skew Similar method for Series.
pandas.DataFrame.skew Similar method for DataFrame.

pandas.core.window.rolling.Rolling.kurt

Rolling.**kurt**(***kwargs*)

Calculate unbiased rolling kurtosis.

This function uses Fisher's definition of kurtosis without bias.

Parameters

****kwargs** Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.kurt Equivalent method for Series.
pandas.DataFrame.kurt Equivalent method for DataFrame.
scipy.stats.skew Third moment of a probability density.
scipy.stats.kurtosis Reference SciPy method.

Notes

A minimum of 4 periods is required for the rolling calculation.

Examples

The example below will show a rolling calculation with a window size of four matching the equivalent function call using *scipy.stats*.

```
>>> arr = [1, 2, 3, 4, 999]
>>> import scipy.stats
>>> print(f"{scipy.stats.kurtosis(arr[:-1], bias=False):.6f}")
-1.200000
>>> print(f"{scipy.stats.kurtosis(arr[1:], bias=False):.6f}")
3.999946
>>> s = pd.Series(arr)
>>> s.rolling(4).kurt()
0         NaN
1         NaN
2         NaN
3   -1.200000
4    3.999946
dtype: float64
```

pandas.core.window.rolling.Rolling.apply

Rolling.**apply**(*func*, *raw=False*, *engine=None*, *engine_kwargs=None*, *args=None*, *kwargs=None*)

Apply an arbitrary function to each rolling window.

Parameters

func [function] Must produce a single value from an ndarray input if `raw=True` or a single value from a Series if `raw=False`. Can also accept a Numba JIT function with `engine='numba'` specified.

Changed in version 1.0.0.

raw [bool, default None]

- `False` : passes each row or column as a Series to the function.
- `True` : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

engine [str, default None]

- `'cython'` : Runs rolling apply through C-extensions from cython.
- `'numba'` : Runs rolling apply through JIT compiled code from numba. Only available when `raw` is set to `True`.
- `None` : Defaults to `'cython'` or globally setting `compute.use_numba`

New in version 1.0.0.

engine_kwargs [dict, default None]

- For `'cython'` engine, there are no accepted `engine_kwargs`
- For `'numba'` engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the `'numba'` engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to both the `func` and the `apply` rolling aggregation.

New in version 1.0.0.

args [tuple, default None] Positional arguments to be passed into func.

kwargs [dict, default None] Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrame data.
pandas.Series.apply Similar method for Series.
pandas.DataFrame.apply Similar method for DataFrame.

Notes

See *Numba engine* for extended documentation and performance considerations for the Numba engine.

pandas.core.window.rolling.Rolling.aggregate

Rolling.**aggregate**(*func*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series/Dataframe or when passed to Series/Dataframe.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrame data.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6], "C": [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9
```

```
>>> df.rolling(2).sum()
     A     B     C
0  NaN   NaN   NaN
1  3.0   9.0  15.0
2  5.0  11.0  17.0
```

```
>>> df.rolling(2).agg({"A": "sum", "B": "min"})
     A    B
0  NaN  NaN
1  3.0  4.0
2  5.0  5.0
```

pandas.core.window.rolling.Rolling.quantile

Rolling.**quantile**(*quantile*, *interpolation='linear'*, ***kwargs*)

Calculate the rolling quantile.

Parameters

quantile [float] Quantile to compute. 0 <= quantile <= 1.

interpolation [{'linear', 'lower', 'higher', 'midpoint', 'nearest'}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points *i* and *j*:

- linear: *i* + (*j* - *i*) * *fraction*, where *fraction* is the fractional part of the index surrounded by *i* and *j*.
- lower: *i*.
- higher: *j*.
- nearest: *i* or *j* whichever is nearest.
- midpoint: (*i* + *j*) / 2.

****kwargs** For compatibility with other rolling methods. Has no effect on the result.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.quantile Computes value at the given quantile over all data in Series.
pandas.DataFrame.quantile Computes values at the given quantile over requested axis in DataFrame.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0    NaN
1    1.0
2    2.0
3    3.0
dtype: float64
```

```
>>> s.rolling(2).quantile(.4, interpolation='midpoint')
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64
```

pandas.core.window.rolling.Rolling.sem

Rolling.**sem**(*ddof=1*, **args*, ***kwargs*)

Compute rolling standard error of mean.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.sem Equivalent method for Series.
pandas.DataFrame.sem Equivalent method for DataFrame.

Notes

A minimum of one period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([0, 1, 2, 3])
>>> s.rolling(2, min_periods=1).sem()
0         NaN
1    0.707107
2    0.707107
3    0.707107
dtype: float64
```

```
>>> s.expanding().sem()
0         NaN
1    0.707107
2    0.707107
3    0.745356
dtype: float64
```

3.9.2 Weighted window functions

Window.mean(*args, **kwargs)	Calculate the window mean of the values.
Window.sum(*args, **kwargs)	Calculate window sum of given DataFrame or Series.
Window.var([ddof])	Calculate unbiased window variance.
Window.std([ddof])	Calculate window standard deviation.

pandas.core.window.rolling.Window.mean

Window.**mean**(**args*, ***kwargs*)

Calculate the window mean of the values.

Parameters

***args** Under Review.

****kwargs** Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the window calculation.

See also:

pandas.Series.window Calling object with Series data.
pandas.DataFrame.window Calling object with DataFrames.
pandas.Series.mean Equivalent method for Series.
pandas.DataFrame.mean Equivalent method for DataFrame.

Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64
```

```
>>> s.rolling(3).mean()
0    NaN
1    NaN
2    2.0
3    3.0
dtype: float64
```

pandas.core.window.rolling.Window.sum

Window.**sum**(**args*, ***kwargs*)

Calculate window sum of given DataFrame or Series.

Parameters

***args, **kwargs** For compatibility with other window methods. Has no effect on the computed value.

Returns

Series or DataFrame Same type as the input, with the same index, containing the window sum.

See also:

pandas.Series.sum Reducing sum for Series.
pandas.DataFrame.sum Reducing sum for DataFrame.

Examples

```
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

```
>>> s.rolling(3).sum()
0     NaN
1     NaN
2     6.0
3     9.0
4    12.0
dtype: float64
```

```
>>> s.expanding(3).sum()
0     NaN
1     NaN
2     6.0
3    10.0
4    15.0
dtype: float64
```

```
>>> s.rolling(3, center=True).sum()
0     NaN
1     6.0
2     9.0
3    12.0
4     NaN
dtype: float64
```

For DataFrame, each window sum is computed column-wise.

```
>>> df = pd.DataFrame({"A": s, "B": s ** 2})
>>> df
   A   B
0  1   1
1  2   4
2  3   9
3  4  16
4  5  25
```

```
>>> df.rolling(3).sum()
      A     B
0   NaN   NaN
1   NaN   NaN
2   6.0  14.0
3   9.0  29.0
4  12.0  50.0
```

pandas.core.window.rolling.Window.var

Window.**var**(*ddof=1*, **args*, ***kwargs*)

Calculate unbiased window variance.

New in version 1.0.0.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the window calculation.

See also:

pandas.Series.window Calling object with Series data.
pandas.DataFrame.window Calling object with DataFrames.
pandas.Series.var Equivalent method for Series.
pandas.DataFrame.var Equivalent method for DataFrame.
numpy.var Equivalent method for Numpy array.

Notes

The default *ddof* of 1 used in `Series.var()` is different than the default *ddof* of 0 in `numpy.var()`.

A minimum of 1 period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0         NaN
1         NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).var()
0         NaN
1         NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

pandas.core.window.rolling.Window.std

Window.**std**(*ddof=1*, **args*, ***kwargs*)

Calculate window standard deviation.

New in version 1.0.0.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the window calculation.

See also:

pandas.Series.window Calling object with Series data.
pandas.DataFrame.window Calling object with DataFrames.
pandas.Series.std Equivalent method for Series.
pandas.DataFrame.std Equivalent method for DataFrame.
numpy.std Equivalent method for Numpy array.

Notes

The default *ddof* of 1 used in Series.std is different than the default *ddof* of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0         NaN
1         NaN
2    0.577350
3    1.000000
4    1.000000
5    1.154701
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).std()
0         NaN
1         NaN
2    0.577350
3    0.957427
4    0.894427
5    0.836660
6    0.786796
dtype: float64
```

3.9.3 Expanding window functions

Expanding.count()	The expanding count of any non-NaN observations inside the window.
Expanding.sum(*args, **kwargs)	Calculate expanding sum of given DataFrame or Series.
Expanding.mean(*args, **kwargs)	Calculate the expanding mean of the values.
Expanding.median(**kwargs)	Calculate the expanding median.
Expanding.var([ddof])	Calculate unbiased expanding variance.
Expanding.std([ddof])	Calculate expanding standard deviation.
Expanding.min(*args, **kwargs)	Calculate the expanding minimum.
Expanding.max(*args, **kwargs)	Calculate the expanding maximum.
Expanding.corr([other, pairwise])	Calculate expanding correlation.
Expanding.cov([other, pairwise, ddof])	Calculate the expanding sample covariance.
Expanding.skew(**kwargs)	Unbiased expanding skewness.
Expanding.kurt(**kwargs)	Calculate unbiased expanding kurtosis.
Expanding.apply(func[, raw, engine, ...])	Apply an arbitrary function to each expanding window.
Expanding.aggregate(func, *args, **kwargs)	Aggregate using one or more operations over the specified axis.
Expanding.quantile(quantile[, interpolation])	Calculate the expanding quantile.
Expanding.sem([ddof])	Compute expanding standard error of mean.

pandas.core.window.expanding.Expanding.count

Expanding.**count**()

The expanding count of any non-NaN observations inside the window.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.DataFrame.count Count of the full DataFrame.

Examples

```
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0    1.0
1    2.0
2    1.0
3    1.0
dtype: float64
>>> s.rolling(3).count()
0    1.0
1    2.0
2    2.0
3    2.0
dtype: float64
>>> s.rolling(4).count()
0    1.0
1    2.0
2    2.0
3    3.0
dtype: float64
```

pandas.core.window.expanding.Expanding.sum

Expanding.**sum**(**args*, ***kwargs*)

Calculate expanding sum of given DataFrame or Series.

Parameters

***args, **kwargs** For compatibility with other expanding methods. Has no effect on the computed value.

Returns

Series or DataFrame Same type as the input, with the same index, containing the expanding sum.

See also:

pandas.Series.sum Reducing sum for Series.
pandas.DataFrame.sum Reducing sum for DataFrame.

Examples

```
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

```
>>> s.rolling(3).sum()
0     NaN
1     NaN
2     6.0
3     9.0
4    12.0
dtype: float64
```

```
>>> s.expanding(3).sum()
0     NaN
1     NaN
2     6.0
3    10.0
4    15.0
dtype: float64
```

```
>>> s.rolling(3, center=True).sum()
0     NaN
1     6.0
2     9.0
3    12.0
4     NaN
dtype: float64
```

For DataFrame, each expanding sum is computed column-wise.

```
>>> df = pd.DataFrame({"A": s, "B": s ** 2})
>>> df
   A   B
0  1   1
1  2   4
2  3   9
3  4  16
4  5  25
```

```
>>> df.rolling(3).sum()
      A     B
0   NaN   NaN
1   NaN   NaN
2   6.0  14.0
3   9.0  29.0
4  12.0  50.0
```

pandas.core.window.expanding.Expanding.mean

Expanding.**mean**(**args*, ***kwargs*)

Calculate the expanding mean of the values.

Parameters

***args** Under Review.

****kwargs** Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.Series.mean Equivalent method for Series.
pandas.DataFrame.mean Equivalent method for DataFrame.

Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64
```

```
>>> s.rolling(3).mean()
0    NaN
1    NaN
2    2.0
3    3.0
dtype: float64
```

pandas.core.window.expanding.Expanding.median

Expanding.**median**(***kwargs*)

Calculate the expanding median.

Parameters

****kwargs** For compatibility with other expanding methods. Has no effect on the computed median.

Returns

Series or DataFrame Returned type is the same as the original object.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.Series.median Equivalent method for Series.
pandas.DataFrame.median Equivalent method for DataFrame.

Examples

Compute the rolling median of a series with a window size of 3.

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0    NaN
1    NaN
2    1.0
3    2.0
4    3.0
dtype: float64
```

pandas.core.window.expanding.Expanding.var

Expanding.**var**(*ddof=1*, **args*, ***kwargs*)

Calculate unbiased expanding variance.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.Series.var Equivalent method for Series.
pandas.DataFrame.var Equivalent method for DataFrame.
numpy.var Equivalent method for Numpy array.

Notes

The default *ddof* of 1 used in `Series.var()` is different than the default *ddof* of 0 in `numpy.var()`.

A minimum of 1 period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0         NaN
1         NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).var()
0         NaN
1         NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

pandas.core.window.expanding.Expanding.std

Expanding.**std**(*ddof=1*, **args*, ***kwargs*)

Calculate expanding standard deviation.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.Series.std Equivalent method for Series.
pandas.DataFrame.std Equivalent method for DataFrame.
numpy.std Equivalent method for Numpy array.

Notes

The default *ddof* of 1 used in Series.std is different than the default *ddof* of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0         NaN
1         NaN
2    0.577350
3    1.000000
4    1.000000
5    1.154701
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).std()
0         NaN
1         NaN
2    0.577350
3    0.957427
4    0.894427
5    0.836660
6    0.786796
dtype: float64
```

pandas.core.window.expanding.Expanding.min

Expanding.**min**(**args*, ***kwargs*)

Calculate the expanding minimum.

Parameters

****kwargs** Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with a Series.
pandas.DataFrame.expanding Calling object with a DataFrame.
pandas.Series.min Similar method for Series.
pandas.DataFrame.min Similar method for DataFrame.

Examples

Performing a rolling minimum with a window size of 3.

```
>>> s = pd.Series([4, 3, 5, 2, 6])
>>> s.rolling(3).min()
0    NaN
1    NaN
2    3.0
3    2.0
4    2.0
dtype: float64
```

pandas.core.window.expanding.Expanding.max

Expanding.**max**(**args*, ***kwargs*)

Calculate the expanding maximum.

Parameters

***args, **kwargs** Arguments and keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.expanding Calling object with Series data.

pandas.DataFrame.expanding Calling object with DataFrame data.
pandas.Series.max Similar method for Series.
pandas.DataFrame.max Similar method for DataFrame.

pandas.core.window.expanding.Expanding.corr

Expanding.**corr**(*other=None*, *pairwise=None*, ***kwargs*)

Calculate expanding correlation.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self.

pairwise [bool, default None] Calculate pairwise combinations of columns within a DataFrame. If *other* is not specified, defaults to *True*, otherwise defaults to *False*. Not relevant for *Series*.

****kwargs** Unused.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.Series.corr Equivalent method for Series.
pandas.DataFrame.corr Equivalent method for DataFrame.
cov Similar method to calculate covariance.
numpy.corrcoef NumPy Pearson's correlation calculation.

Notes

This function uses Pearson's definition of correlation (https://en.wikipedia.org/wiki/Pearson_correlation_coefficient).

When *other* is not specified, the output will be self correlation (e.g. all 1's), except for *DataFrame* inputs with *pairwise* set to *True*.

Function will return `NaN` for correlations of equal valued sequences; this is the result of a 0/0 division error.

When *pairwise* is set to *False*, only matching columns between *self* and *other* will be used.

When *pairwise* is set to *True*, the output will be a MultiIndex DataFrame with the original index on the first level, and the *other* DataFrame columns on the second level.

In the case of missing elements, only complete pairwise observations will be used.

Examples

The below example shows a rolling calculation with a window size of four matching the equivalent function call using `numpy.corrcoef()`.

```
>>> v1 = [3, 3, 3, 5, 8]
>>> v2 = [3, 4, 4, 4, 8]
>>> # numpy returns a 2X2 array, the correlation coefficient
>>> # is the number at entry [0][1]
>>> print(f"{np.corrcoef(v1[:-1], v2[:-1])[0][1]:.6f}")
0.333333
>>> print(f"{np.corrcoef(v1[1:], v2[1:])[0][1]:.6f}")
0.916949
>>> s1 = pd.Series(v1)
>>> s2 = pd.Series(v2)
>>> s1.rolling(4).corr(s2)
0         NaN
1         NaN
2         NaN
3    0.333333
4    0.916949
dtype: float64
```

The below example shows a similar rolling calculation on a DataFrame using the pairwise option.

```
>>> matrix = np.array([[51., 35.], [49., 30.], [47., 32.],    [46., 31.], [50.,␣
↪36.]])
>>> print(np.corrcoef(matrix[:-1,0], matrix[:-1,1]).round(7))
[[1.         0.6263001]
 [0.6263001  1.       ]]
>>> print(np.corrcoef(matrix[1:,0], matrix[1:,1]).round(7))
[[1.         0.5553681]
 [0.5553681  1.       ]]
>>> df = pd.DataFrame(matrix, columns=['X','Y'])
>>> df
      X     Y
0  51.0  35.0
1  49.0  30.0
2  47.0  32.0
3  46.0  31.0
4  50.0  36.0
>>> df.rolling(4).corr(pairwise=True)
            X         Y
0 X       NaN       NaN
  Y       NaN       NaN
1 X       NaN       NaN
  Y       NaN       NaN
2 X       NaN       NaN
  Y       NaN       NaN
3 X  1.000000  0.626300
  Y  0.626300  1.000000
4 X  1.000000  0.555368
  Y  0.555368  1.000000
```

pandas.core.window.expanding.Expanding.cov

Expanding.**cov**(*other=None*, *pairwise=None*, *ddof=1*, ***kwargs*)

Calculate the expanding sample covariance.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

pairwise [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndexed DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

****kwargs** Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrame data.
pandas.Series.cov Similar method for Series.
pandas.DataFrame.cov Similar method for DataFrame.

pandas.core.window.expanding.Expanding.skew

Expanding.**skew**(***kwargs*)

Unbiased expanding skewness.

Parameters

****kwargs** Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrame data.
pandas.Series.skew Similar method for Series.
pandas.DataFrame.skew Similar method for DataFrame.

pandas.core.window.expanding.Expanding.kurt

Expanding.**kurt**(***kwargs*)

Calculate unbiased expanding kurtosis.

This function uses Fisher's definition of kurtosis without bias.

Parameters

****kwargs** Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding	Calling object with Series data.
pandas.DataFrame.expanding	Calling object with DataFrames.
pandas.Series.kurt	Equivalent method for Series.
pandas.DataFrame.kurt	Equivalent method for DataFrame.
scipy.stats.skew	Third moment of a probability density.
scipy.stats.kurtosis	Reference SciPy method.

Notes

A minimum of 4 periods is required for the expanding calculation.

Examples

The example below will show an expanding calculation with a window size of four matching the equivalent function call using *scipy.stats*.

```
>>> arr = [1, 2, 3, 4, 999]
>>> import scipy.stats
>>> print(f"{scipy.stats.kurtosis(arr[:-1], bias=False):.6f}")
-1.200000
>>> print(f"{scipy.stats.kurtosis(arr, bias=False):.6f}")
4.999874
>>> s = pd.Series(arr)
>>> s.expanding(4).kurt()
0         NaN
1         NaN
2         NaN
3   -1.200000
4    4.999874
dtype: float64
```

pandas.core.window.expanding.Expanding.apply

Expanding.**apply**(*func*, *raw=False*, *engine=None*, *engine_kwargs=None*, *args=None*, *kwargs=None*)

Apply an arbitrary function to each expanding window.

Parameters

func [function] Must produce a single value from an ndarray input if `raw=True` or a single value from a Series if `raw=False`. Can also accept a Numba JIT function with `engine='numba'` specified.

Changed in version 1.0.0.

raw [bool, default None]

- `False` : passes each row or column as a Series to the function.
- `True` : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

engine [str, default None]

- `'cython'` : Runs rolling apply through C-extensions from cython.

- `'numba'` : Runs rolling apply through JIT compiled code from numba. Only available when `raw` is set to `True`.
- `None` : Defaults to `'cython'` or globally setting `compute.use_numba`

  New in version 1.0.0.

engine_kwargs [dict, default None]

- For `'cython'` engine, there are no accepted `engine_kwargs`
- For `'numba'` engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the `'numba'` engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to both the `func` and the `apply` rolling aggregation.

  New in version 1.0.0.

args [tuple, default None] Positional arguments to be passed into func.

kwargs [dict, default None] Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrame data.
pandas.Series.apply Similar method for Series.
pandas.DataFrame.apply Similar method for DataFrame.

Notes

See *Numba engine* for extended documentation and performance considerations for the Numba engine.

pandas.core.window.expanding.Expanding.aggregate

`Expanding.`**`aggregate`**(*func*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series/Dataframe or when passed to Series/Dataframe.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

pandas.DataFrame.aggregate Similar DataFrame method.
pandas.Series.aggregate Similar Series method.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6], "C": [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9
```

```
>>> df.ewm(alpha=0.5).mean()
          A         B         C
0  1.000000  4.000000  7.000000
1  1.666667  4.666667  7.666667
2  2.428571  5.428571  8.428571
```

pandas.core.window.expanding.Expanding.quantile

Expanding.**quantile**(*quantile*, *interpolation='linear'*, ***kwargs*)

Calculate the expanding quantile.

Parameters

quantile [float] Quantile to compute. 0 <= quantile <= 1.

interpolation [{'linear', 'lower', 'higher', 'midpoint', 'nearest'}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points *i* and *j*:

- linear: *i* + (*j* - *i*) * *fraction*, where *fraction* is the fractional part of the index surrounded by *i* and *j*.
- lower: *i*.
- higher: *j*.
- nearest: *i* or *j* whichever is nearest.
- midpoint: (*i* + *j*) / 2.

****kwargs** For compatibility with other expanding methods. Has no effect on the result.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.quantile Computes value at the given quantile over all data in Series.
pandas.DataFrame.quantile Computes values at the given quantile over requested axis in DataFrame.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0    NaN
1    1.0
2    2.0
3    3.0
dtype: float64
```

```
>>> s.rolling(2).quantile(.4, interpolation='midpoint')
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64
```

pandas.core.window.expanding.Expanding.sem

`Expanding.`**`sem`**(*ddof=1*, **args*, ***kwargs*)

Compute expanding standard error of mean.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

***args, **kwargs** For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.Series.sem Equivalent method for Series.
pandas.DataFrame.sem Equivalent method for DataFrame.

Notes

A minimum of one period is required for the rolling calculation.

Examples

```
>>> s = pd.Series([0, 1, 2, 3])
>>> s.rolling(2, min_periods=1).sem()
0         NaN
1    0.707107
2    0.707107
3    0.707107
dtype: float64
```

```
>>> s.expanding().sem()
0         NaN
1    0.707107
2    0.707107
3    0.745356
dtype: float64
```

3.9.4 Exponentially-weighted window functions

ExponentialMovingWindow.mean(*args, **kwargs)	Exponential weighted moving average.
ExponentialMovingWindow.std([bias])	Exponential weighted moving stddev.
ExponentialMovingWindow.var([bias])	Exponential weighted moving variance.
ExponentialMovingWindow.corr([other, pairwise])	Exponential weighted sample correlation.
ExponentialMovingWindow.cov([other, ...])	Exponential weighted sample covariance.

pandas.core.window.ewm.ExponentialMovingWindow.mean

ExponentialMovingWindow.**mean**(**args*, ***kwargs*)

Exponential weighted moving average.

Parameters

***args, **kwargs** Arguments and keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.ewm Calling object with Series data.
pandas.DataFrame.ewm Calling object with DataFrame data.
pandas.Series.mean Similar method for Series.
pandas.DataFrame.mean Similar method for DataFrame.

pandas.core.window.ewm.ExponentialMovingWindow.std

ExponentialMovingWindow.**std**(*bias=False*, **args*, ***kwargs*)

Exponential weighted moving stddev.

Parameters

bias [bool, default False] Use a standard estimation bias correction.

***args, **kwargs** Arguments and keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.ewm Calling object with Series data.
pandas.DataFrame.ewm Calling object with DataFrame data.
pandas.Series.std Similar method for Series.
pandas.DataFrame.std Similar method for DataFrame.

pandas.core.window.ewm.ExponentialMovingWindow.var

ExponentialMovingWindow.**var**(*bias=False*, **args*, ***kwargs*)

Exponential weighted moving variance.

Parameters

bias [bool, default False] Use a standard estimation bias correction.

***args, **kwargs** Arguments and keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.ewm Calling object with Series data.
pandas.DataFrame.ewm Calling object with DataFrame data.
pandas.Series.var Similar method for Series.
pandas.DataFrame.var Similar method for DataFrame.

pandas.core.window.ewm.ExponentialMovingWindow.corr

ExponentialMovingWindow.**corr**(*other=None*, *pairwise=None*, ***kwargs*)

Exponential weighted sample correlation.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

pairwise [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

****kwargs** Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.ewm Calling object with Series data.
pandas.DataFrame.ewm Calling object with DataFrame data.
pandas.Series.corr Similar method for Series.
pandas.DataFrame.corr Similar method for DataFrame.

pandas.core.window.ewm.ExponentialMovingWindow.cov

ExponentialMovingWindow.**cov**(*other=None*, *pairwise=None*, *bias=False*, ***kwargs*)

Exponential weighted sample covariance.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

pairwise [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

bias [bool, default False] Use a standard estimation bias correction.

****kwargs** Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.ewm Calling object with Series data.
pandas.DataFrame.ewm Calling object with DataFrame data.
pandas.Series.cov Similar method for Series.
pandas.DataFrame.cov Similar method for DataFrame.

3.9.5 Window indexer

Base class for defining custom window boundaries.

api.indexers.BaseIndexer([index_array, ...])	Base class for window bounds calculations.
api.indexers.FixedForwardWindowIndexer([...])	Creates window boundaries for fixed-length windows that include the current row.
api.indexers.VariableOffsetWindowIndexer([...])	Calculate window boundaries based on a non-fixed offset such as a BusinessDay

pandas.api.indexers.BaseIndexer

class pandas.api.indexers.**BaseIndexer**(*index_array=None*, *window_size=0*, ***kwargs*)
Base class for window bounds calculations.

Methods

get_window_bounds([num_values, min_periods, ...])	Computes the bounds of a window.

pandas.api.indexers.BaseIndexer.get_window_bounds

BaseIndexer.**get_window_bounds**(*num_values=0*, *min_periods=None*, *center=None*, *closed=None*)
Computes the bounds of a window.

Parameters

num_values [int, default 0] number of values that will be aggregated over

window_size [int, default 0] the number of rows in a window

min_periods [int, default None] min_periods passed from the top level rolling API

center [bool, default None] center passed from the top level rolling API

closed [str, default None] closed passed from the top level rolling API

win_type [str, default None] win_type passed from the top level rolling API

Returns

A tuple of ndarray[int64]s, indicating the boundaries of each

window

pandas.api.indexers.FixedForwardWindowIndexer

class pandas.api.indexers.**FixedForwardWindowIndexer**(*index_array=None*, *window_size=0*, ***kwargs*)
Creates window boundaries for fixed-length windows that include the current row.

Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

```
>>> indexer = pd.api.indexers.FixedForwardWindowIndexer(window_size=2)
>>> df.rolling(window=indexer, min_periods=1).sum()
     B
0  1.0
1  3.0
2  2.0
3  4.0
4  4.0
```

Methods

get_window_bounds([num_values, min_periods, ...])	Computes the bounds of a window.

pandas.api.indexers.FixedForwardWindowIndexer.get_window_bounds

FixedForwardWindowIndexer.**get_window_bounds**(*num_values=0*, *min_periods=None*, *center=None*, *closed=None*)

Computes the bounds of a window.

Parameters

num_values [int, default 0] number of values that will be aggregated over

window_size [int, default 0] the number of rows in a window

min_periods [int, default None] min_periods passed from the top level rolling API

center [bool, default None] center passed from the top level rolling API

closed [str, default None] closed passed from the top level rolling API

win_type [str, default None] win_type passed from the top level rolling API

Returns

A tuple of ndarray[int64]s, indicating the boundaries of each

window

pandas.api.indexers.VariableOffsetWindowIndexer

class pandas.api.indexers.**VariableOffsetWindowIndexer**(*index_array=None*, *window_size=0*, *index=None*, *offset=None*, ***kwargs*)

Calculate window boundaries based on a non-fixed offset such as a BusinessDay

Methods

get_window_bounds([num_values, min_periods, ...])	Computes the bounds of a window.

pandas.api.indexers.VariableOffsetWindowIndexer.get_window_bounds

VariableOffsetWindowIndexer.**get_window_bounds**(*num_values=0*, *min_periods=None*, *center=None*, *closed=None*)

Computes the bounds of a window.

Parameters

num_values [int, default 0] number of values that will be aggregated over

window_size [int, default 0] the number of rows in a window

min_periods [int, default None] min_periods passed from the top level rolling API

center [bool, default None] center passed from the top level rolling API

closed [str, default None] closed passed from the top level rolling API

win_type [str, default None] win_type passed from the top level rolling API

Returns

A tuple of ndarray[int64]s, indicating the boundaries of each

window

3.10 GroupBy

GroupBy objects are returned by groupby calls: *pandas.DataFrame.groupby()*, *pandas.Series.groupby()*, etc.

3.10.1 Indexing, iteration

GroupBy.__iter__()	Groupby iterator.
GroupBy.groups	Dict {group name -> group labels}.
GroupBy.indices	Dict {group name -> group indices}.
GroupBy.get_group(name[, obj])	Construct DataFrame from group with provided name.

pandas.core.groupby.GroupBy.__iter__

GroupBy.**__iter__**()
Groupby iterator.

Returns

Generator yielding sequence of (name, subsetted object)

for each group

pandas.core.groupby.GroupBy.groups

property GroupBy.**groups**
Dict {group name -> group labels}.

pandas.core.groupby.GroupBy.indices

property GroupBy.**indices**
Dict {group name -> group indices}.

pandas.core.groupby.GroupBy.get_group

GroupBy.**get_group**(*name*, *obj=None*)
Construct DataFrame from group with provided name.

Parameters

name [object] The name of the group to get as a DataFrame.

obj [DataFrame, default None] The DataFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used.

Returns

group [same type as obj]

Grouper(*args, **kwargs)	A Grouper allows the user to specify a groupby instruction for an object.

pandas.Grouper

class pandas.**Grouper**(**args*, ***kwargs*)
A Grouper allows the user to specify a groupby instruction for an object.

This specification will select a column via the key parameter, or if the level and/or axis parameters are given, a level of the index of the target object.

If *axis* and/or *level* are passed as keywords to both *Grouper* and *groupby*, the values passed to *Grouper* take precedence.

Parameters

key [str, defaults to None] Groupby key, which selects the grouping column of the target.

level [name/number, defaults to None] The level for the target index.

freq [str / frequency object, defaults to None] This will groupby the specified frequency if the target selection (via key or level) is a datetime-like object. For full specification of

available frequencies, please see here.

axis [str, int, defaults to 0] Number/name of the axis.

sort [bool, default to False] Whether to sort the resulting labels.

closed [{'left' or 'right'}] Closed end of interval. Only when *freq* parameter is passed.

label [{'left' or 'right'}] Interval boundary to use for labeling. Only when *freq* parameter is passed.

convention [{'start', 'end', 'e', 's'}] If grouper is PeriodIndex and *freq* parameter is passed.

base [int, default 0] Only when *freq* parameter is passed. For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0.

Deprecated since version 1.1.0: The new arguments that you should use are 'offset' or 'origin'.

loffset [str, DateOffset, timedelta object] Only when *freq* parameter is passed.

Deprecated since version 1.1.0: loffset is only working for `.resample(...)` and not for Grouper (GH28302). However, loffset is also deprecated for `.resample(...)` See: *DataFrame.resample*

origin [{'epoch', 'start', 'start_day'}, Timestamp or str, default 'start_day'] The timestamp on which to adjust the grouping. The timezone of origin must match the timezone of the index. If a timestamp is not used, these values are also supported:

- 'epoch': *origin* is 1970-01-01
- 'start': *origin* is the first value of the timeseries
- 'start_day': *origin* is the first day at midnight of the timeseries

New in version 1.1.0.

offset [Timedelta or str, default is None] An offset timedelta added to the origin.

New in version 1.1.0.

dropna [bool, default True] If True, and if group keys contain NA values, NA values together with row/column will be dropped. If False, NA values will also be treated as the key in groups.

New in version 1.2.0.

Returns

A specification for a groupby instruction

Examples

Syntactic sugar for `df.groupby('A')`

```
>>> df = pd.DataFrame(
...     {
...         "Animal": ["Falcon", "Parrot", "Falcon", "Falcon", "Parrot"],
...         "Speed": [100, 5, 200, 300, 15],
...     }
... )
>>> df
```

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```
   Animal  Speed
0  Falcon    100
1  Parrot      5
2  Falcon    200
3  Falcon    300
4  Parrot     15
>>> df.groupby(pd.Grouper(key="Animal")).mean()
        Speed
Animal
Falcon    200
Parrot     10
```

Specify a resample operation on the column 'Publish date'

```
>>> df = pd.DataFrame(
...     {
...         "Publish date": [
...              pd.Timestamp("2000-01-02"),
...              pd.Timestamp("2000-01-02"),
...              pd.Timestamp("2000-01-09"),
...              pd.Timestamp("2000-01-16")
...          ],
...          "ID": [0, 1, 2, 3],
...          "Price": [10, 20, 30, 40]
...      }
... )
>>> df
  Publish date  ID  Price
0   2000-01-02   0     10
1   2000-01-02   1     20
2   2000-01-09   2     30
3   2000-01-16   3     40
>>> df.groupby(pd.Grouper(key="Publish date", freq="1W")).mean()
                ID  Price
Publish date
2000-01-02    0.5   15.0
2000-01-09    2.0   30.0
2000-01-16    3.0   40.0
```

If you want to adjust the start of the bins based on a fixed timestamp:

```
>>> start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'
>>> rng = pd.date_range(start, end, freq='7min')
>>> ts = pd.Series(np.arange(len(rng)) * 3, index=rng)
>>> ts
2000-10-01 23:30:00     0
2000-10-01 23:37:00     3
2000-10-01 23:44:00     6
2000-10-01 23:51:00     9
2000-10-01 23:58:00    12
2000-10-02 00:05:00    15
2000-10-02 00:12:00    18
2000-10-02 00:19:00    21
2000-10-02 00:26:00    24
Freq: 7T, dtype: int64
```

```
>>> ts.groupby(pd.Grouper(freq='17min')).sum()
2000-10-01 23:14:00     0
2000-10-01 23:31:00     9
2000-10-01 23:48:00    21
2000-10-02 00:05:00    54
2000-10-02 00:22:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.groupby(pd.Grouper(freq='17min', origin='epoch')).sum()
2000-10-01 23:18:00     0
2000-10-01 23:35:00    18
2000-10-01 23:52:00    27
2000-10-02 00:09:00    39
2000-10-02 00:26:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.groupby(pd.Grouper(freq='17min', origin='2000-01-01')).sum()
2000-10-01 23:24:00     3
2000-10-01 23:41:00    15
2000-10-01 23:58:00    45
2000-10-02 00:15:00    45
Freq: 17T, dtype: int64
```

If you want to adjust the start of the bins with an *offset* Timedelta, the two following lines are equivalent:

```
>>> ts.groupby(pd.Grouper(freq='17min', origin='start')).sum()
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

```
>>> ts.groupby(pd.Grouper(freq='17min', offset='23h30min')).sum()
2000-10-01 23:30:00     9
2000-10-01 23:47:00    21
2000-10-02 00:04:00    54
2000-10-02 00:21:00    24
Freq: 17T, dtype: int64
```

To replace the use of the deprecated *base* argument, you can now use *offset*, in this example it is equivalent to have *base=2*:

```
>>> ts.groupby(pd.Grouper(freq='17min', offset='2min')).sum()
2000-10-01 23:16:00     0
2000-10-01 23:33:00     9
2000-10-01 23:50:00    36
2000-10-02 00:07:00    39
2000-10-02 00:24:00    24
Freq: 17T, dtype: int64
```

Attributes

ax	
groups	

3.10.2 Function application

`GroupBy.apply`(func, *args, **kwargs)	Apply function *func* group-wise and combine the results together.
`GroupBy.agg`(func, *args, **kwargs)	
`SeriesGroupBy.aggregate`([func, engine, ...])	Aggregate using one or more operations over the specified axis.
`DataFrameGroupBy.aggregate`([func, engine, ...])	Aggregate using one or more operations over the specified axis.
`SeriesGroupBy.transform`(func, *args[, ...])	Call function producing a like-indexed Series on each group and return a Series having the same indexes as the original object filled with the transformed values
`DataFrameGroupBy.transform`(func, *args[, ...])	Call function producing a like-indexed DataFrame on each group and return a DataFrame having the same indexes as the original object filled with the transformed values
`GroupBy.pipe`(func, *args, **kwargs)	Apply a function *func* with arguments to this GroupBy object and return the function's result.

pandas.core.groupby.GroupBy.apply

GroupBy.**apply**(*func*, **args*, ***kwargs*)

Apply function *func* group-wise and combine the results together.

The function passed to *apply* must take a dataframe as its first argument and return a DataFrame, Series or scalar. *apply* will then take care of combining the results back together into a single dataframe or series. *apply* is therefore a highly flexible grouping method.

While *apply* is a very flexible method, its downside is that using it can be quite a bit slower than using more specific methods like *agg* or *transform*. Pandas offers a wide range of method that will be much faster than using *apply* for their specific purposes, so try to use them before reaching for *apply*.

Parameters

func [callable] A callable that takes a dataframe as its first argument, and returns a dataframe, a series or a scalar. In addition the callable may take positional and keyword arguments.

args, kwargs [tuple and dict] Optional positional and keyword arguments to pass to *func*.

Returns

applied [Series or DataFrame]

See also:

pipe Apply function to the full GroupBy object instead of to each group.
aggregate Apply aggregate function to the GroupBy object.
transform Apply function column-by-column to the GroupBy object.
Series.apply Apply a function to a Series.
DataFrame.apply Apply a function to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.agg

GroupBy.**agg**(*func*, **args*, ***kwargs*)

pandas.core.groupby.SeriesGroupBy.aggregate

SeriesGroupBy.**aggregate**(*func=None*, **args*, *engine=None*, *engine_kwargs=None*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

Can also accept a Numba JIT function with `engine='numba'` specified. Only passing a single function is supported with this engine.

If the `'numba'` engine is chosen, the function must be a user defined function with `values` and `index` as the first and second arguments respectively in the function signature. Each group's index will be passed to the user defined function and optionally available for use.

Changed in version 1.1.0.

***args** Positional arguments to pass to func.

engine [str, default None]

- `'cython'` : Runs the function through C-extensions from cython.
- `'numba'` : Runs the function through JIT compiled code from numba.
- `None` : Defaults to `'cython'` or globally setting `compute.use_numba`

New in version 1.1.0.

engine_kwargs [dict, default None]

- For `'cython'` engine, there are no accepted `engine_kwargs`
- For `'numba'` engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the `'numba'` engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to the function

New in version 1.1.0.

****kwargs** Keyword arguments to be passed into func.

Returns

Series

See also:

Series.groupby.apply Apply function func group-wise and combine the results together.

Series.groupby.transform Aggregate using one or more operations over the specified axis.
Series.aggregate Transforms the Series on each group based on the given function.

Notes

When using `engine='numba'`, there will be no "fall back" behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Examples

```
>>> s = pd.Series([1, 2, 3, 4])
```

```
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.groupby([1, 1, 2, 2]).min()
1    1
2    3
dtype: int64
```

```
>>> s.groupby([1, 1, 2, 2]).agg('min')
1    1
2    3
dtype: int64
```

```
>>> s.groupby([1, 1, 2, 2]).agg(['min', 'max'])
   min  max
1    1    2
2    3    4
```

The output column names can be controlled by passing the desired column names and aggregations as keyword arguments.

```
>>> s.groupby([1, 1, 2, 2]).agg(
...     minimum='min',
...     maximum='max',
... )
   minimum  maximum
1        1        2
2        3        4
```

pandas.core.groupby.DataFrameGroupBy.aggregate

DataFrameGroupBy.**aggregate**(*func=None*, **args*, *engine=None*, *engine_kwargs=None*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

Can also accept a Numba JIT function with `engine='numba'` specified. Only passing a single function is supported with this engine.

If the `'numba'` engine is chosen, the function must be a user defined function with `values` and `index` as the first and second arguments respectively in the function signature. Each group's index will be passed to the user defined function and optionally available for use.

Changed in version 1.1.0.

***args** Positional arguments to pass to func.

engine [str, default None]

- `'cython'` : Runs the function through C-extensions from cython.
- `'numba'` : Runs the function through JIT compiled code from numba.
- `None` : Defaults to `'cython'` or globally setting `compute.use_numba`

New in version 1.1.0.

engine_kwargs [dict, default None]

- For `'cython'` engine, there are no accepted `engine_kwargs`
- For `'numba'` engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the `'numba'` engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to the function

New in version 1.1.0.

****kwargs** Keyword arguments to be passed into func.

Returns

DataFrame

See also:

DataFrame.groupby.apply Apply function func group-wise and combine the results together.
DataFrame.groupby.transform Aggregate using one or more operations over the specified axis.
DataFrame.aggregate Transforms the Series on each group based on the given function.

Notes

When using `engine='numba'`, there will be no "fall back" behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Examples

```
>>> df = pd.DataFrame(
...     {
...         "A": [1, 1, 2, 2],
...         "B": [1, 2, 3, 4],
...         "C": [0.362838, 0.227877, 1.267767, -0.562860],
...     }
... )
```

```
>>> df
   A  B         C
0  1  1  0.362838
1  1  2  0.227877
2  2  3  1.267767
3  2  4 -0.562860
```

The aggregation is for each column.

```
>>> df.groupby('A').agg('min')
   B         C
A
1  1  0.227877
2  3 -0.562860
```

Multiple aggregations

```
>>> df.groupby('A').agg(['min', 'max'])
    B             C
  min max       min       max
A
1   1   2  0.227877  0.362838
2   3   4 -0.562860  1.267767
```

Select a column for aggregation

```
>>> df.groupby('A').B.agg(['min', 'max'])
   min  max
A
1    1    2
2    3    4
```

Different aggregations per column

```
>>> df.groupby('A').agg({'B': ['min', 'max'], 'C': 'sum'})
    B             C
  min max       sum
A
1   1   2  0.590715
2   3   4  0.704907
```

To control the output names with different aggregations per column, pandas supports "named aggregation"

```
>>> df.groupby("A").agg(
...     b_min=pd.NamedAgg(column="B", aggfunc="min"),
...     c_sum=pd.NamedAgg(column="C", aggfunc="sum"))
   b_min     c_sum
A
1      1  0.590715
2      3  0.704907
```

- The keywords are the *output* column names
- The values are tuples whose first element is the column to select and the second element is the aggregation to apply to that column. Pandas provides the `pandas.NamedAgg` namedtuple with the fields `['column', 'aggfunc']` to make it clearer what the arguments are. As usual, the aggregation can be a callable or a string alias.

See *Named aggregation* for more.

pandas.core.groupby.SeriesGroupBy.transform

`SeriesGroupBy.`**`transform`**(*func*, **args*, *engine=None*, *engine_kwargs=None*, ***kwargs*)

Call function producing a like-indexed Series on each group and return a Series having the same indexes as the original object filled with the transformed values

Parameters

f [function] Function to apply to each group.

Can also accept a Numba JIT function with `engine='numba'` specified.

If the `'numba'` engine is chosen, the function must be a user defined function with `values` and `index` as the first and second arguments respectively in the function signature. Each group's index will be passed to the user defined function and optionally available for use.

Changed in version 1.1.0.

***args** Positional arguments to pass to func.

engine [str, default None]

- `'cython'` : Runs the function through C-extensions from cython.
- `'numba'` : Runs the function through JIT compiled code from numba.
- `None` : Defaults to `'cython'` or globally setting `compute.use_numba`

New in version 1.1.0.

engine_kwargs [dict, default None]

- For `'cython'` engine, there are no accepted `engine_kwargs`
- For `'numba'` engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the `'numba'` engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to the function

New in version 1.1.0.

****kwargs** Keyword arguments to be passed into func.

Returns

Series

See also:

`Series.groupby.apply` Apply function func group-wise and combine the results together.
`Series.groupby.aggregate` Aggregate using one or more operations over the specified axis.
`Series.transform` Transforms the Series on each group based on the given function.

Notes

Each group is endowed the attribute 'name' in case you need to know which group you are working on.

The current implementation imposes three requirements on f:

- f must return a value that either has the same shape as the input subframe or can be broadcast to the shape of the input subframe. For example, if *f* returns a scalar it will be broadcast to have the same shape as the input subframe.
- if this is a DataFrame, f must support application column-by-column in the subframe. If f also supports application to the entire subframe, then a fast path is used starting from the second chunk.
- f must not mutate groups. Mutation is not supported and may produce unexpected results.

When using `engine='numba'`, there will be no "fall back" behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Examples

```
>>> df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
...                           'foo', 'bar'],
...                    'B' : ['one', 'one', 'two', 'three',
...                           'two', 'two'],
...                    'C' : [1, 5, 5, 2, 5, 5],
...                    'D' : [2.0, 5., 8., 1., 2., 9.]})
>>> grouped = df.groupby('A')
>>> grouped.transform(lambda x: (x - x.mean()) / x.std())
          C         D
0 -1.154701 -0.577350
1  0.577350  0.000000
2  0.577350  1.154701
3 -1.154701 -1.000000
4  0.577350 -0.577350
5  0.577350  1.000000
```

Broadcast result of the transformation

```
>>> grouped.transform(lambda x: x.max() - x.min())
   C    D
0  4  6.0
1  3  8.0
2  4  6.0
3  3  8.0
4  4  6.0
5  3  8.0
```

pandas.core.groupby.DataFrameGroupBy.transform

DataFrameGroupBy.**transform**(*func*, **args*, *engine=None*, *engine_kwargs=None*, ***kwargs*)

Call function producing a like-indexed DataFrame on each group and return a DataFrame having the same indexes as the original object filled with the transformed values

Parameters

f [function] Function to apply to each group.

Can also accept a Numba JIT function with `engine='numba'` specified.

If the `'numba'` engine is chosen, the function must be a user defined function with `values` and `index` as the first and second arguments respectively in the function signature. Each group's index will be passed to the user defined function and optionally available for use.

Changed in version 1.1.0.

***args** Positional arguments to pass to func.

engine [str, default None]

- `'cython'` : Runs the function through C-extensions from cython.
- `'numba'` : Runs the function through JIT compiled code from numba.
- `None` : Defaults to `'cython'` or globally setting `compute.use_numba`

New in version 1.1.0.

engine_kwargs [dict, default None]

- For `'cython'` engine, there are no accepted `engine_kwargs`
- For `'numba'` engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the `'numba'` engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to the function

New in version 1.1.0.

****kwargs** Keyword arguments to be passed into func.

Returns

DataFrame

See also:

DataFrame.groupby.apply Apply function func group-wise and combine the results together.
DataFrame.groupby.aggregate Aggregate using one or more operations over the specified axis.
DataFrame.transform Transforms the Series on each group based on the given function.

Notes

Each group is endowed the attribute 'name' in case you need to know which group you are working on.

The current implementation imposes three requirements on f:

- f must return a value that either has the same shape as the input subframe or can be broadcast to the shape of the input subframe. For example, if *f* returns a scalar it will be broadcast to have the same shape as the input subframe.
- if this is a DataFrame, f must support application column-by-column in the subframe. If f also supports application to the entire subframe, then a fast path is used starting from the second chunk.
- f must not mutate groups. Mutation is not supported and may produce unexpected results.

When using `engine='numba'`, there will be no "fall back" behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Examples

```
>>> df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
...                           'foo', 'bar'],
...                    'B' : ['one', 'one', 'two', 'three',
...                           'two', 'two'],
...                    'C' : [1, 5, 5, 2, 5, 5],
...                    'D' : [2.0, 5., 8., 1., 2., 9.]})
>>> grouped = df.groupby('A')
>>> grouped.transform(lambda x: (x - x.mean()) / x.std())
          C         D
0 -1.154701 -0.577350
1  0.577350  0.000000
2  0.577350  1.154701
3 -1.154701 -1.000000
4  0.577350 -0.577350
5  0.577350  1.000000
```

Broadcast result of the transformation

```
>>> grouped.transform(lambda x: x.max() - x.min())
   C    D
0  4  6.0
1  3  8.0
2  4  6.0
3  3  8.0
4  4  6.0
5  3  8.0
```

pandas.core.groupby.GroupBy.pipe

`GroupBy.`**`pipe`**(*func*, **args*, ***kwargs*)

Apply a function *func* with arguments to this GroupBy object and return the function's result.

Use *.pipe* when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing

```
>>> h(g(f(df.groupby('group')), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.groupby('group')
...    .pipe(f)
...    .pipe(g, arg1=a)
...    .pipe(h, arg2=b, arg3=c))
```

which is much more readable.

Parameters

func [callable or tuple of (callable, str)] Function to apply to this GroupBy object or, alternatively, a *(callable, data_keyword)* tuple where *data_keyword* is a string indicating the keyword of *callable* that expects the GroupBy object.

args [iterable, optional] Positional arguments passed into *func*.

kwargs [dict, optional] A dictionary of keyword arguments passed into *func*.

Returns

object [the return type of *func*.]

See also:

`Series.pipe` Apply a function with arguments to a series.
`DataFrame.pipe` Apply a function with arguments to a dataframe.
`apply` Apply function to each group instead of to the full GroupBy object.

Notes

See more here

Examples

```
>>> df = pd.DataFrame({'A': 'a b a b'.split(), 'B': [1, 2, 3, 4]})
>>> df
   A  B
0  a  1
1  b  2
2  a  3
3  b  4
```

To get the difference between each groups maximum and minimum value in one pass, you can do

```
>>> df.groupby('A').pipe(lambda x: x.max() - x.min())
   B
A
a  2
b  2
```

3.10.3 Computations / descriptive stats

GroupBy.all([skipna])	Return True if all values in the group are truthful, else False.
GroupBy.any([skipna])	Return True if any value in the group is truthful, else False.
GroupBy.bfill([limit])	Backward fill the values.
GroupBy.backfill([limit])	Backward fill the values.
GroupBy.count()	Compute count of group, excluding missing values.
GroupBy.cumcount([ascending])	Number each item in each group from 0 to the length of that group - 1.
GroupBy.cummax([axis])	Cumulative max for each group.
GroupBy.cummin([axis])	Cumulative min for each group.
GroupBy.cumprod([axis])	Cumulative product for each group.
GroupBy.cumsum([axis])	Cumulative sum for each group.
GroupBy.ffill([limit])	Forward fill the values.
GroupBy.first([numeric_only, min_count])	Compute first of group values.
GroupBy.head([n])	Return first n rows of each group.
GroupBy.last([numeric_only, min_count])	Compute last of group values.
GroupBy.max([numeric_only, min_count])	Compute max of group values.
GroupBy.mean([numeric_only])	Compute mean of groups, excluding missing values.
GroupBy.median([numeric_only])	Compute median of groups, excluding missing values.
GroupBy.min([numeric_only, min_count])	Compute min of group values.
GroupBy.ngroup([ascending])	Number each group from 0 to the number of groups - 1.
GroupBy.nth(n[, dropna])	Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.
GroupBy.ohlc()	Compute open, high, low and close values of a group, excluding missing values.
GroupBy.pad([limit])	Forward fill the values.
GroupBy.prod([numeric_only, min_count])	Compute prod of group values.
GroupBy.rank([method, ascending, na_option, ...])	Provide the rank of values within each group.
GroupBy.pct_change([periods, fill_method, ...])	Calculate pct_change of each value to previous entry in group.
GroupBy.size()	Compute group sizes.
GroupBy.sem([ddof])	Compute standard error of the mean of groups, excluding missing values.
GroupBy.std([ddof])	Compute standard deviation of groups, excluding missing values.
GroupBy.sum([numeric_only, min_count])	Compute sum of group values.
GroupBy.var([ddof])	Compute variance of groups, excluding missing values.
GroupBy.tail([n])	Return last n rows of each group.

pandas.core.groupby.GroupBy.all

GroupBy.**all**(*skipna=True*)

Return True if all values in the group are truthful, else False.

Parameters

skipna [bool, default True] Flag to ignore nan values during truth testing.

Returns

Series or DataFrame DataFrame or Series of boolean values, where a value is True if all elements are True within its respective group, False otherwise.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.any

GroupBy.**any**(*skipna=True*)

Return True if any value in the group is truthful, else False.

Parameters

skipna [bool, default True] Flag to ignore nan values during truth testing.

Returns

Series or DataFrame DataFrame or Series of boolean values, where a value is True if any element is True within its respective group, False otherwise.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.bfill

GroupBy.**bfill**(*limit=None*)

Backward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.backfill Backward fill the missing values in the dataset.
DataFrame.backfill Backward fill the missing values in the dataset.
Series.fillna Fill NaN values of a Series.
DataFrame.fillna Fill NaN values of a DataFrame.

pandas.core.groupby.GroupBy.backfill

GroupBy.**backfill**(*limit=None*)

Backward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.backfill Backward fill the missing values in the dataset.
DataFrame.backfill Backward fill the missing values in the dataset.
Series.fillna Fill NaN values of a Series.
DataFrame.fillna Fill NaN values of a DataFrame.

pandas.core.groupby.GroupBy.count

GroupBy.**count**()

Compute count of group, excluding missing values.

Returns

Series or DataFrame Count of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.cumcount

GroupBy.**cumcount**(*ascending=True*)

Number each item in each group from 0 to the length of that group - 1.

Essentially this is equivalent to

```
self.apply(lambda x: pd.Series(np.arange(len(x)), x.index))
```

Parameters

ascending [bool, default True] If False, number in reverse, from length of group - 1 to 0.

Returns

Series Sequence number of each element within each group.

See also:

ngroup Number the groups themselves.

Examples

```
>>> df = pd.DataFrame([['a'], ['a'], ['a'], ['b'], ['b'], ['a']],
...                   columns=['A'])
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').cumcount()
0    0
1    1
2    2
3    0
4    1
5    3
dtype: int64
>>> df.groupby('A').cumcount(ascending=False)
0    3
1    2
2    1
3    1
4    0
5    0
dtype: int64
```

pandas.core.groupby.GroupBy.cummax

GroupBy.**cummax**(*axis=0*, ***kwargs*)

Cumulative max for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.cummin

GroupBy.**cummin**(*axis=0*, ***kwargs*)

Cumulative min for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.cumprod

GroupBy.**cumprod**(*axis=0*, **args*, ***kwargs*)

Cumulative product for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.cumsum

GroupBy.**cumsum**(*axis=0*, **args*, ***kwargs*)

Cumulative sum for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.ffill

GroupBy.**ffill**(*limit=None*)

Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.pad Returns Series with minimum number of char in object.
DataFrame.pad Object with missing values filled or None if inplace=True.
Series.fillna Fill NaN values of a Series.
DataFrame.fillna Fill NaN values of a DataFrame.

pandas.core.groupby.GroupBy.first

GroupBy.**first**(*numeric_only=False*, *min_count=- 1*)

Compute first of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed first of values within each group.

pandas.core.groupby.GroupBy.head

GroupBy.**head**(*n=5*)

Return first n rows of each group.

Similar to `.apply(lambda x: x.head(n))`, but it returns a subset of rows from the original DataFrame with original index and order preserved (`as_index` flag is ignored).

Does not work for negative values of *n*.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

Examples

```
>>> df = pd.DataFrame([[1, 2], [1, 4], [5, 6]],
...                   columns=['A', 'B'])
>>> df.groupby('A').head(1)
   A  B
0  1  2
2  5  6
>>> df.groupby('A').head(-1)
Empty DataFrame
Columns: [A, B]
Index: []
```

pandas.core.groupby.GroupBy.last

GroupBy.**last**(*numeric_only=False*, *min_count=- 1*)

Compute last of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed last of values within each group.

pandas.core.groupby.GroupBy.max

GroupBy.**max**(*numeric_only=False*, *min_count=- 1*)

Compute max of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed max of values within each group.

pandas.core.groupby.GroupBy.mean

GroupBy.**mean**(*numeric_only=True*)

Compute mean of groups, excluding missing values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

Returns

pandas.Series or pandas.DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

Examples

```
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],
...                    'B': [np.nan, 2, 3, 4, 5],
...                    'C': [1, 2, 1, 1, 2]}, columns=['A', 'B', 'C'])
```

Groupby one column and return the mean of the remaining columns in each group.

```
>>> df.groupby('A').mean()
     B         C
A
1  3.0  1.333333
2  4.0  1.500000
```

Groupby two columns and return the mean of the remaining column.

```
>>> df.groupby(['A', 'B']).mean()
       C
A B
1 2.0  2
  4.0  1
2 3.0  1
  5.0  2
```

Groupby one column and return the mean of only particular column in the group.

```
>>> df.groupby('A')['B'].mean()
A
1    3.0
2    4.0
Name: B, dtype: float64
```

pandas.core.groupby.GroupBy.median

GroupBy.**median**(*numeric_only=True*)

Compute median of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

Returns

Series or DataFrame Median of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.min

GroupBy.**min**(*numeric_only=False*, *min_count=- 1*)

Compute min of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed min of values within each group.

pandas.core.groupby.GroupBy.ngroup

GroupBy.**ngroup**(*ascending=True*)

Number each group from 0 to the number of groups - 1.

This is the enumerative complement of cumcount. Note that the numbers given to the groups match the order in which the groups would be seen when iterating over the groupby object, not the order they are first observed.

Parameters

ascending [bool, default True] If False, number in reverse, from number of group - 1 to 0.

Returns

Series Unique numbers for each group.

See also:

cumcount Number the rows in each group.

Examples

```
>>> df = pd.DataFrame({"A": list("aaabba")})
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').ngroup()
0    0
1    0
2    0
3    1
4    1
5    0
dtype: int64
>>> df.groupby('A').ngroup(ascending=False)
0    1
1    1
2    1
3    0
4    0
5    1
dtype: int64
>>> df.groupby(["A", [1,1,2,3,2,1]]).ngroup()
0    0
1    0
2    1
3    3
4    2
5    0
dtype: int64
```

pandas.core.groupby.GroupBy.nth

GroupBy.**nth**(*n*, *dropna=None*)

Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.

If dropna, will take the nth non-null row, dropna is either 'all' or 'any'; this is equivalent to calling dropna(how=dropna) before the groupby.

Parameters

n [int or list of ints] A single nth value for the row or a list of nth values.

dropna [None or str, optional] Apply the specified dropna operation before counting which row is the nth row. Needs to be None, 'any' or 'all'.

Returns

Series or DataFrame N-th value within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

Examples

```
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],
...                    'B': [np.nan, 2, 3, 4, 5]}, columns=['A', 'B'])
>>> g = df.groupby('A')
>>> g.nth(0)
     B
A
1  NaN
2  3.0
>>> g.nth(1)
     B
A
1  2.0
2  5.0
>>> g.nth(-1)
     B
A
1  4.0
2  5.0
>>> g.nth([0, 1])
     B
A
1  NaN
1  2.0
2  3.0
2  5.0
```

Specifying *dropna* allows count ignoring `NaN`

```
>>> g.nth(0, dropna='any')
     B
A
1  2.0
2  3.0
```

NaNs denote group exhausted when using dropna

```
>>> g.nth(3, dropna='any')
    B
A
1 NaN
2 NaN
```

Specifying *as_index=False* in *groupby* keeps the original index.

```
>>> df.groupby('A', as_index=False).nth(1)
   A    B
1  1  2.0
4  2  5.0
```

pandas.core.groupby.GroupBy.ohlc

GroupBy.**ohlc**()

Compute open, high, low and close values of a group, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

Returns

DataFrame Open, high, low and close values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.pad

GroupBy.**pad**(*limit=None*)

Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.pad Returns Series with minimum number of char in object.
DataFrame.pad Object with missing values filled or None if inplace=True.
Series.fillna Fill NaN values of a Series.
DataFrame.fillna Fill NaN values of a DataFrame.

pandas.core.groupby.GroupBy.prod

GroupBy.**prod**(*numeric_only=True*, *min_count=0*)

Compute prod of group values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed prod of values within each group.

pandas.core.groupby.GroupBy.rank

GroupBy.**rank**(*method='average'*, *ascending=True*, *na_option='keep'*, *pct=False*, *axis=0*)

Provide the rank of values within each group.

Parameters

method [{'average', 'min', 'max', 'first', 'dense'}, default 'average']

- average: average rank of group.
- min: lowest rank in group.
- max: highest rank in group.
- first: ranks assigned in order they appear in the array.
- dense: like 'min', but rank always increases by 1 between groups.

ascending [bool, default True] False for ranks by high (1) to low (N).

na_option [{'keep', 'top', 'bottom'}, default 'keep']

- keep: leave NA values where they are.
- top: smallest rank if ascending.
- bottom: smallest rank if descending.

pct [bool, default False] Compute percentage rank of data within each group.

axis [int, default 0] The axis of the object over which to compute the rank.

Returns

DataFrame with ranking of values within each group

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.pct_change

GroupBy.**pct_change**(*periods=1*, *fill_method='pad'*, *limit=None*, *freq=None*, *axis=0*)

Calculate pct_change of each value to previous entry in group.

Returns

Series or DataFrame Percentage changes within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.size

GroupBy.**size**()

Compute group sizes.

Returns

DataFrame or Series Number of rows in each group as a Series if as_index is True or a DataFrame if as_index is False.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.sem

GroupBy.**sem**(*ddof=1*)

Compute standard error of the mean of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

Parameters

ddof [int, default 1] Degrees of freedom.

Returns

Series or DataFrame Standard error of the mean of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.std

GroupBy.**std**(*ddof=1*)

Compute standard deviation of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

Parameters

ddof [int, default 1] Degrees of freedom.

Returns

Series or DataFrame Standard deviation of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.sum

GroupBy.**sum**(*numeric_only=True*, *min_count=0*)

Compute sum of group values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed sum of values within each group.

pandas.core.groupby.GroupBy.var

GroupBy.**var**(*ddof=1*)

Compute variance of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

Parameters

ddof [int, default 1] Degrees of freedom.

Returns

Series or DataFrame Variance of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.GroupBy.tail

GroupBy.**tail**(*n=5*)

Return last n rows of each group.

Similar to `.apply(lambda x: x.tail(n))`, but it returns a subset of rows from the original DataFrame with original index and order preserved (`as_index` flag is ignored).

Does not work for negative values of *n*.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

Examples

```
>>> df = pd.DataFrame([['a', 1], ['a', 2], ['b', 1], ['b', 2]],
...                   columns=['A', 'B'])
>>> df.groupby('A').tail(1)
   A  B
1  a  2
3  b  2
>>> df.groupby('A').tail(-1)
Empty DataFrame
Columns: [A, B]
Index: []
```

The following methods are available in both `SeriesGroupBy` and `DataFrameGroupBy` objects, but may differ slightly, usually in that the `DataFrameGroupBy` version usually permits the specification of an axis argument, and often an argument indicating whether to restrict application to columns of a specific data type.

DataFrameGroupBy.all([skipna])	Return True if all values in the group are truthful, else False.
DataFrameGroupBy.any([skipna])	Return True if any value in the group is truthful, else False.
DataFrameGroupBy.backfill([limit])	Backward fill the values.
DataFrameGroupBy.bfill([limit])	Backward fill the values.
DataFrameGroupBy.corr	Compute pairwise correlation of columns, excluding NA/null values.
DataFrameGroupBy.count()	Compute count of group, excluding missing values.
DataFrameGroupBy.cov	Compute pairwise covariance of columns, excluding NA/null values.
DataFrameGroupBy.cumcount([ascending])	Number each item in each group from 0 to the length of that group - 1.
DataFrameGroupBy.cummax([axis])	Cumulative max for each group.
DataFrameGroupBy.cummin([axis])	Cumulative min for each group.
DataFrameGroupBy.cumprod([axis])	Cumulative product for each group.
DataFrameGroupBy.cumsum([axis])	Cumulative sum for each group.
DataFrameGroupBy.describe(**kwargs)	Generate descriptive statistics.
DataFrameGroupBy.diff	First discrete difference of element.
DataFrameGroupBy.ffill([limit])	Forward fill the values.
DataFrameGroupBy.fillna	Fill NA/NaN values using the specified method.
DataFrameGroupBy.filter(func[, dropna])	Return a copy of a DataFrame excluding filtered elements.
DataFrameGroupBy.hist	Make a histogram of the DataFrame's.
DataFrameGroupBy.idxmax([axis, skipna])	Return index of first occurrence of maximum over requested axis.
DataFrameGroupBy.idxmin([axis, skipna])	Return index of first occurrence of minimum over requested axis.
DataFrameGroupBy.mad	Return the mean absolute deviation of the values over the requested axis.
DataFrameGroupBy.nunique([dropna])	Return DataFrame with counts of unique elements in each position.
DataFrameGroupBy.pad([limit])	Forward fill the values.
DataFrameGroupBy.pct_change([periods, ...])	Calculate pct_change of each value to previous entry in group.

continues on next page

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DataFrameGroupBy.plot	Class implementing the .plot attribute for groupby objects.
DataFrameGroupBy.quantile([q, interpolation])	Return group values at the given quantile, a la numpy.percentile.
DataFrameGroupBy.rank([method, ascending, ...])	Provide the rank of values within each group.
DataFrameGroupBy.resample(rule, *args, **kwargs)	Provide resampling when using a TimeGrouper.
DataFrameGroupBy.sample([n, frac, replace, ...])	Return a random sample of items from each group.
DataFrameGroupBy.shift([periods, freq, ...])	Shift each group by periods observations.
DataFrameGroupBy.size()	Compute group sizes.
DataFrameGroupBy.skew	Return unbiased skew over requested axis.
DataFrameGroupBy.take	Return the elements in the given *positional* indices along an axis.
DataFrameGroupBy.tshift	(DEPRECATED) Shift the time index, using the index's frequency if available.

pandas.core.groupby.DataFrameGroupBy.all

DataFrameGroupBy.**all**(*skipna=True*)

Return True if all values in the group are truthful, else False.

Parameters

skipna [bool, default True] Flag to ignore nan values during truth testing.

Returns

Series or DataFrame DataFrame or Series of boolean values, where a value is True if all elements are True within its respective group, False otherwise.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.any

DataFrameGroupBy.**any**(*skipna=True*)

Return True if any value in the group is truthful, else False.

Parameters

skipna [bool, default True] Flag to ignore nan values during truth testing.

Returns

Series or DataFrame DataFrame or Series of boolean values, where a value is True if any element is True within its respective group, False otherwise.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.backfill

DataFrameGroupBy.**backfill**(*limit=None*)

Backward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.backfill Backward fill the missing values in the dataset.
DataFrame.backfill Backward fill the missing values in the dataset.
Series.fillna Fill NaN values of a Series.
DataFrame.fillna Fill NaN values of a DataFrame.

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pandas.core.groupby.DataFrameGroupBy.corr

property DataFrameGroupBy.**corr**

Compute pairwise correlation of columns, excluding NA/null values.

Parameters

method [{'pearson', 'kendall', 'spearman'} or callable] Method of correlation:

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- **callable: callable with input two 1d ndarrays** and returning a float. Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable's behavior.

  New in version 0.24.0.

min_periods [int, optional] Minimum number of observations required per pair of columns to have a valid result. Currently only available for Pearson and Spearman correlation.

Returns

DataFrame Correlation matrix.

See also:

DataFrame.corrwith Compute pairwise correlation with another DataFrame or Series.
Series.corr Compute the correlation between two Series.

Examples

```
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
>>> df = pd.DataFrame([(.2, .3), (.0, .6), (.6, .0), (.2, .1)],
...                   columns=['dogs', 'cats'])
>>> df.corr(method=histogram_intersection)
      dogs  cats
dogs   1.0   0.3
cats   0.3   1.0
```

pandas.core.groupby.DataFrameGroupBy.count

DataFrameGroupBy.**count**()

Compute count of group, excluding missing values.

Returns

DataFrame Count of values within each group.

pandas.core.groupby.DataFrameGroupBy.cov

property DataFrameGroupBy.**cov**

Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the covariance matrix of the columns of the DataFrame.

Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as `NaN`.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

Parameters

min_periods [int, optional] Minimum number of observations required per pair of columns to have a valid result.

ddof [int, default 1] Delta degrees of freedom. The divisor used in calculations is `N - ddof`, where `N` represents the number of elements.

New in version 1.1.0.

Returns

DataFrame The covariance matrix of the series of the DataFrame.

See also:

Series.cov Compute covariance with another Series.
core.window.ExponentialMovingWindow.cov Exponential weighted sample covariance.

core.window.Expanding.cov Expanding sample covariance.
core.window.Rolling.cov Rolling sample covariance.

Notes

Returns the covariance matrix of the DataFrame's time series. The covariance is normalized by N-ddof.

For DataFrames that have Series that are missing data (assuming that data is missing at random) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

Examples

```
>>> df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],
...                   columns=['dogs', 'cats'])
>>> df.cov()
          dogs      cats
dogs  0.666667 -1.000000
cats -1.000000  1.666667
```

```
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(1000, 5),
...                   columns=['a', 'b', 'c', 'd', 'e'])
>>> df.cov()
          a         b         c         d         e
a  0.998438 -0.020161  0.059277 -0.008943  0.014144
b -0.020161  1.059352 -0.008543 -0.024738  0.009826
c  0.059277 -0.008543  1.010670 -0.001486 -0.000271
d -0.008943 -0.024738 -0.001486  0.921297 -0.013692
e  0.014144  0.009826 -0.000271 -0.013692  0.977795
```

Minimum number of periods

This method also supports an optional `min_periods` keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(20, 3),
...                   columns=['a', 'b', 'c'])
>>> df.loc[df.index[:5], 'a'] = np.nan
>>> df.loc[df.index[5:10], 'b'] = np.nan
>>> df.cov(min_periods=12)
          a         b         c
a  0.316741       NaN -0.150812
b       NaN  1.248003  0.191417
c -0.150812  0.191417  0.895202
```

pandas.core.groupby.DataFrameGroupBy.cumcount

DataFrameGroupBy.**cumcount**(*ascending=True*)

Number each item in each group from 0 to the length of that group - 1.

Essentially this is equivalent to

```
self.apply(lambda x: pd.Series(np.arange(len(x)), x.index))
```

Parameters

ascending [bool, default True] If False, number in reverse, from length of group - 1 to 0.

Returns

Series Sequence number of each element within each group.

See also:

ngroup Number the groups themselves.

Examples

```
>>> df = pd.DataFrame([['a'], ['a'], ['a'], ['b'], ['b'], ['a']],
...                   columns=['A'])
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').cumcount()
0    0
1    1
2    2
3    0
4    1
5    3
dtype: int64
>>> df.groupby('A').cumcount(ascending=False)
0    3
1    2
2    1
3    1
4    0
5    0
dtype: int64
```

pandas.core.groupby.DataFrameGroupBy.cummax

DataFrameGroupBy.**cummax**(*axis=0*, ***kwargs*)

Cumulative max for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.cummin

DataFrameGroupBy.**cummin**(*axis=0*, ***kwargs*)

Cumulative min for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.cumprod

DataFrameGroupBy.**cumprod**(*axis=0*, **args*, ***kwargs*)

Cumulative product for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.cumsum

DataFrameGroupBy.**cumsum**(*axis=0*, **args*, ***kwargs*)

Cumulative sum for each group.

Returns

Series or DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.describe

DataFrameGroupBy.**describe**(***kwargs*)

Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

Parameters

percentiles [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

include ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for Series. Here are the options:

- 'all' : All columns of the input will be included in the output.
- A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit numpy.number. To limit it instead to object columns submit the numpy.object data type. Strings can also be used in the style of select_dtypes (e.g. df.describe(include=['O'])). To select pandas categorical columns, use 'category'
- None (default) : The result will include all numeric columns.

exclude [list-like of dtypes or None (default), optional,] A black list of data types to omit from the result. Ignored for Series. Here are the options:

- A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit numpy.number. To exclude object columns submit the data type numpy.object. Strings can also be used in the style of select_dtypes (e.g. df.describe(include=['O'])). To exclude pandas categorical columns, use 'category'
- None (default) : The result will exclude nothing.

datetime_is_numeric [bool, default False] Whether to treat datetime dtypes as numeric. This affects statistics calculated for the column. For DataFrame input, this also controls whether datetime columns are included by default.

New in version 1.1.0.

Returns

Series or DataFrame Summary statistics of the Series or Dataframe provided.

See also:

DataFrame.count Count number of non-NA/null observations.
DataFrame.max Maximum of the values in the object.
DataFrame.min Minimum of the values in the object.
DataFrame.mean Mean of the values.
DataFrame.std Standard deviation of the observations.
DataFrame.select_dtypes Subset of a DataFrame including/excluding columns based on their dtype.

Notes

For numeric data, the result's index will include `count`, `mean`, `std`, `min`, `max` as well as lower, `50` and upper percentiles. By default the lower percentile is `25` and the upper percentile is `75`. The `50` percentile is the same as the median.

For object data (e.g. strings or timestamps), the result's index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value's frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The *include* and *exclude* parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`.

Examples

Describing a numeric `Series`.

```
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
dtype: float64
```

Describing a categorical `Series`.

```
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count     4
unique    3
top       a
freq      2
dtype: object
```

Describing a timestamp `Series`.

```
>>> s = pd.Series([
...   np.datetime64("2000-01-01"),
...   np.datetime64("2010-01-01"),
...   np.datetime64("2010-01-01")
... ])
>>> s.describe(datetime_is_numeric=True)
count                      3
mean     2006-09-01 08:00:00
```

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```
min      2000-01-01 00:00:00
25%      2004-12-31 12:00:00
50%      2010-01-01 00:00:00
75%      2010-01-01 00:00:00
max      2010-01-01 00:00:00
dtype: object
```

Describing a `DataFrame`. By default only numeric fields are returned.

```
>>> df = pd.DataFrame({'categorical': pd.Categorical(['d','e','f']),
...                    'numeric': [1, 2, 3],
...                    'object': ['a', 'b', 'c']
...                   })
>>> df.describe()
       numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%        1.5
50%        2.0
75%        2.5
max        3.0
```

Describing all columns of a `DataFrame` regardless of data type.

```
>>> df.describe(include='all')
       categorical  numeric object
count            3      3.0      3
unique           3      NaN      3
top              f      NaN      a
freq             1      NaN      1
mean           NaN      2.0    NaN
std            NaN      1.0    NaN
min            NaN      1.0    NaN
25%            NaN      1.5    NaN
50%            NaN      2.0    NaN
75%            NaN      2.5    NaN
max            NaN      3.0    NaN
```

Describing a column from a `DataFrame` by accessing it as an attribute.

```
>>> df.numeric.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a `DataFrame` description.

```
>>> df.describe(include=[np.number])
       numeric
```

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```
count      3.0
mean       2.0
std        1.0
min        1.0
25%        1.5
50%        2.0
75%        2.5
max        3.0
```

Including only string columns in a `DataFrame` description.

```
>>> df.describe(include=[object])
       object
count       3
unique      3
top         a
freq        1
```

Including only categorical columns from a `DataFrame` description.

```
>>> df.describe(include=['category'])
       categorical
count            3
unique           3
top              d
freq             1
```

Excluding numeric columns from a `DataFrame` description.

```
>>> df.describe(exclude=[np.number])
       categorical object
count            3      3
unique           3      3
top              f      a
freq             1      1
```

Excluding object columns from a `DataFrame` description.

```
>>> df.describe(exclude=[object])
       categorical  numeric
count            3      3.0
unique           3      NaN
top              f      NaN
freq             1      NaN
mean           NaN      2.0
std            NaN      1.0
min            NaN      1.0
25%            NaN      1.5
50%            NaN      2.0
75%            NaN      2.5
max            NaN      3.0
```

pandas.core.groupby.DataFrameGroupBy.diff

property DataFrameGroupBy.**diff**

First discrete difference of element.

Calculates the difference of a Dataframe element compared with another element in the Dataframe (default is element in previous row).

Parameters

periods [int, default 1] Periods to shift for calculating difference, accepts negative values.

axis [{0 or 'index', 1 or 'columns'}, default 0] Take difference over rows (0) or columns (1).

Returns

Dataframe First differences of the Series.

See also:

Dataframe.pct_change Percent change over given number of periods.
Dataframe.shift Shift index by desired number of periods with an optional time freq.
Series.diff First discrete difference of object.

Notes

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`. The result is calculated according to current dtype in Dataframe, however dtype of the result is always float64.

Examples

Difference with previous row

```
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
...                    'b': [1, 1, 2, 3, 5, 8],
...                    'c': [1, 4, 9, 16, 25, 36]})
>>> df
   a  b   c
0  1  1   1
1  2  1   4
2  3  2   9
3  4  3  16
4  5  5  25
5  6  8  36
```

```
>>> df.diff()
     a    b     c
0  NaN  NaN   NaN
1  1.0  0.0   3.0
2  1.0  1.0   5.0
3  1.0  1.0   7.0
4  1.0  2.0   9.0
5  1.0  3.0  11.0
```

Difference with previous column

```
>>> df.diff(axis=1)
    a  b   c
0 NaN  0   0
```

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```
1 NaN -1   3
2 NaN -1   7
3 NaN -1  13
4 NaN  0  20
5 NaN  2  28
```

Difference with 3rd previous row

```
>>> df.diff(periods=3)
     a    b     c
0  NaN  NaN   NaN
1  NaN  NaN   NaN
2  NaN  NaN   NaN
3  3.0  2.0  15.0
4  3.0  4.0  21.0
5  3.0  6.0  27.0
```

Difference with following row

```
>>> df.diff(periods=-1)
     a    b     c
0 -1.0  0.0  -3.0
1 -1.0 -1.0  -5.0
2 -1.0 -1.0  -7.0
3 -1.0 -2.0  -9.0
4 -1.0 -3.0 -11.0
5  NaN  NaN   NaN
```

Overflow in input dtype

```
>>> df = pd.DataFrame({'a': [1, 0]}, dtype=np.uint8)
>>> df.diff()
       a
0    NaN
1  255.0
```

pandas.core.groupby.DataFrameGroupBy.ffill

DataFrameGroupBy.**ffill**(*limit=None*)

Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.pad Returns Series with minimum number of char in object.
DataFrame.pad Object with missing values filled or None if inplace=True.
Series.fillna Fill NaN values of a Series.
DataFrame.fillna Fill NaN values of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.fillna

property DataFrameGroupBy.**fillna**

Fill NA/NaN values using the specified method.

Parameters

value [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

method [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use next valid observation to fill gap.

axis [{0 or 'index', 1 or 'columns'}] Axis along which to fill missing values.

inplace [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

downcast [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

Returns

DataFrame or None Object with missing values filled or None if `inplace=True`.

See also:

interpolate Fill NaN values using interpolation.
reindex Conform object to new index.
asfreq Convert TimeSeries to specified frequency.

Examples

```
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                    [3, 4, np.nan, 1],
...                    [np.nan, np.nan, np.nan, 5],
...                    [np.nan, 3, np.nan, 4]],
...                   columns=list('ABCD'))
>>> df
     A    B   C  D
0  NaN  2.0 NaN  0
1  3.0  4.0 NaN  1
2  NaN  NaN NaN  5
3  NaN  3.0 NaN  4
```

Replace all NaN elements with 0s.

```
>>> df.fillna(0)
    A   B   C   D
0   0.0 2.0 0.0 0
```

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```
1   3.0 4.0 0.0 1
2   0.0 0.0 0.0 5
3   0.0 3.0 0.0 4
```

We can also propagate non-null values forward or backward.

```
>>> df.fillna(method='ffill')
    A   B   C   D
0   NaN 2.0 NaN 0
1   3.0 4.0 NaN 1
2   3.0 4.0 NaN 5
3   3.0 3.0 NaN 4
```

Replace all NaN elements in column 'A', 'B', 'C', and 'D', with 0, 1, 2, and 3 respectively.

```
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
    A   B   C   D
0   0.0 2.0 2.0 0
1   3.0 4.0 2.0 1
2   0.0 1.0 2.0 5
3   0.0 3.0 2.0 4
```

Only replace the first NaN element.

```
>>> df.fillna(value=values, limit=1)
    A   B   C   D
0   0.0 2.0 2.0 0
1   3.0 4.0 NaN 1
2   NaN 1.0 NaN 5
3   NaN 3.0 NaN 4
```

pandas.core.groupby.DataFrameGroupBy.filter

DataFrameGroupBy.**filter**(*func*, *dropna=True*, **args*, ***kwargs*)

Return a copy of a DataFrame excluding filtered elements.

Elements from groups are filtered if they do not satisfy the boolean criterion specified by func.

Parameters

func [function] Function to apply to each subframe. Should return True or False.

dropna [Drop groups that do not pass the filter. True by default;] If False, groups that evaluate False are filled with NaNs.

Returns

filtered [DataFrame]

Notes

Each subframe is endowed the attribute 'name' in case you need to know which group you are working on.

Examples

```
>>> df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
...                           'foo', 'bar'],
...                    'B' : [1, 2, 3, 4, 5, 6],
...                    'C' : [2.0, 5., 8., 1., 2., 9.]})
>>> grouped = df.groupby('A')
>>> grouped.filter(lambda x: x['B'].mean() > 3.)
     A  B    C
1  bar  2  5.0
3  bar  4  1.0
5  bar  6  9.0
```

pandas.core.groupby.DataFrameGroupBy.hist

property DataFrameGroupBy.**hist**

Make a histogram of the DataFrame's.

A histogram is a representation of the distribution of data. This function calls `matplotlib.pyplot.hist()`, on each series in the DataFrame, resulting in one histogram per column.

Parameters

data [DataFrame] The pandas object holding the data.

column [str or sequence] If passed, will be used to limit data to a subset of columns.

by [object, optional] If passed, then used to form histograms for separate groups.

grid [bool, default True] Whether to show axis grid lines.

xlabelsize [int, default None] If specified changes the x-axis label size.

xrot [float, default None] Rotation of x axis labels. For example, a value of 90 displays the x labels rotated 90 degrees clockwise.

ylabelsize [int, default None] If specified changes the y-axis label size.

yrot [float, default None] Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.

ax [Matplotlib axes object, default None] The axes to plot the histogram on.

sharex [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in. Note that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure.

sharey [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.

figsize [tuple] The size in inches of the figure to create. Uses the value in *matplotlib.rcParams* by default.

layout [tuple, optional] Tuple of (rows, columns) for the layout of the histograms.

bins [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

legend [bool, default False] Whether to show the legend.

New in version 1.1.0.

****kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.hist()`.

Returns

matplotlib.AxesSubplot or numpy.ndarray of them

See also:

`matplotlib.pyplot.hist` Plot a histogram using matplotlib.

Examples

This example draws a histogram based on the length and width of some animals, displayed in three bins

```
>>> df = pd.DataFrame({
...     'length': [1.5, 0.5, 1.2, 0.9, 3],
...     'width': [0.7, 0.2, 0.15, 0.2, 1.1]
...     }, index=['pig', 'rabbit', 'duck', 'chicken', 'horse'])
>>> hist = df.hist(bins=3)
```

pandas.core.groupby.DataFrameGroupBy.idxmax

`DataFrameGroupBy.`**`idxmax`**(*axis=0*, *skipna=True*)

Return index of first occurrence of maximum over requested axis.

NA/null values are excluded.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns

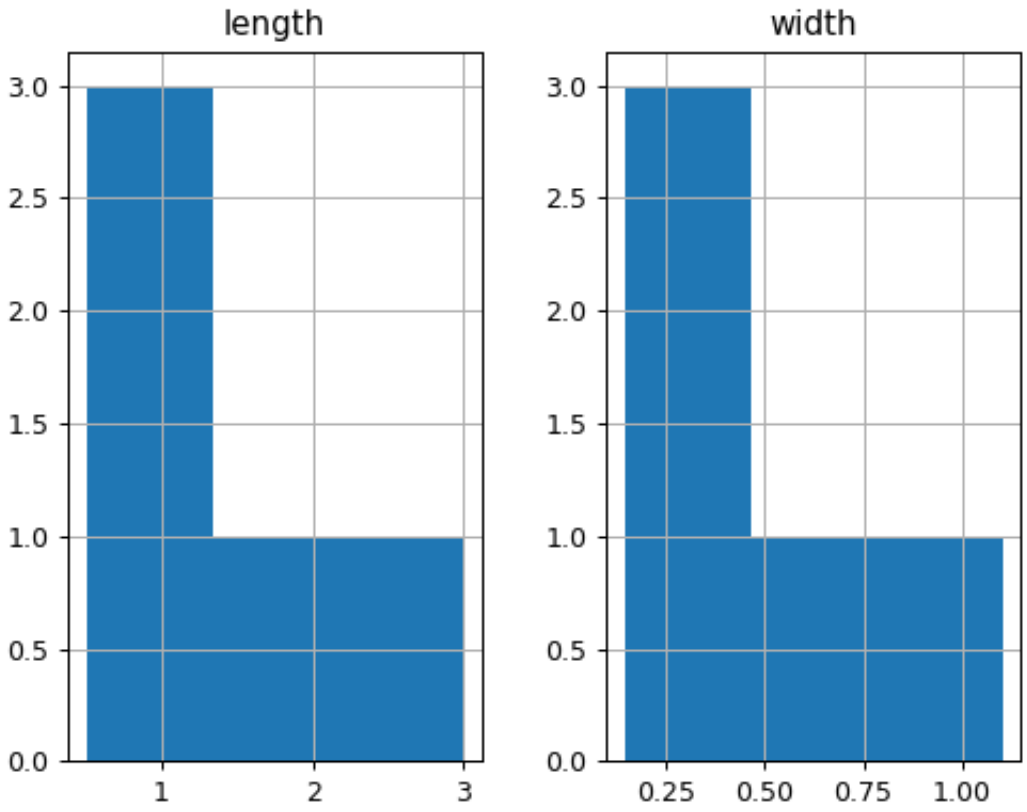
Series Indexes of maxima along the specified axis.

Raises

ValueError

- If the row/column is empty

See also:


length
width
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
0.25
0.50
0.75
1.00

Series.idxmax Return index of the maximum element.

Notes

This method is the DataFrame version of `ndarray.argmax`.

Examples

Consider a dataset containing food consumption in Argentina.

```
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
...                    'co2_emissions': [37.2, 19.66, 1712]},
...                    index=['Pork', 'Wheat Products', 'Beef'])
```

```
>>> df
                consumption  co2_emissions
Pork                  10.51          37.20
Wheat Products       103.11          19.66
Beef                  55.48        1712.00
```

By default, it returns the index for the maximum value in each column.

```
>>> df.idxmax()
consumption     Wheat Products
co2_emissions             Beef
dtype: object
```

To return the index for the maximum value in each row, use `axis="columns"`.

```
>>> df.idxmax(axis="columns")
Pork              co2_emissions
Wheat Products     consumption
Beef              co2_emissions
dtype: object
```

pandas.core.groupby.DataFrameGroupBy.idxmin

DataFrameGroupBy.**idxmin**(*axis=0*, *skipna=True*)

Return index of first occurrence of minimum over requested axis.

NA/null values are excluded.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns

Series Indexes of minima along the specified axis.

Raises

ValueError

- If the row/column is empty

See also:

`Series.idxmin` Return index of the minimum element.

Notes

This method is the DataFrame version of `ndarray.argmin`.

Examples

Consider a dataset containing food consumption in Argentina.

```
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
...                    'co2_emissions': [37.2, 19.66, 1712]},
...                    index=['Pork', 'Wheat Products', 'Beef'])
```

```
>>> df
                consumption  co2_emissions
Pork                  10.51         37.20
Wheat Products       103.11         19.66
Beef                  55.48       1712.00
```

By default, it returns the index for the minimum value in each column.

```
>>> df.idxmin()
consumption                Pork
co2_emissions    Wheat Products
dtype: object
```

To return the index for the minimum value in each row, use `axis="columns"`.

```
>>> df.idxmin(axis="columns")
Pork                consumption
Wheat Products    co2_emissions
Beef                consumption
dtype: object
```

pandas.core.groupby.DataFrameGroupBy.mad

property DataFrameGroupBy.**mad**

Return the mean absolute deviation of the values over the requested axis.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default None] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

Returns

Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.nunique

DataFrameGroupBy.**nunique**(*dropna=True*)

Return DataFrame with counts of unique elements in each position.

Parameters

dropna [bool, default True] Don't include NaN in the counts.

Returns

nunique: DataFrame

Examples

```
>>> df = pd.DataFrame({'id': ['spam', 'egg', 'egg', 'spam',
...                           'ham', 'ham'],
...                    'value1': [1, 5, 5, 2, 5, 5],
...                    'value2': list('abbaxy')})
>>> df
     id  value1 value2
0  spam       1      a
1   egg       5      b
2   egg       5      b
3  spam       2      a
4   ham       5      x
5   ham       5      y
```

```
>>> df.groupby('id').nunique()
      value1  value2
id
egg        1       1
ham        1       2
spam       2       1
```

Check for rows with the same id but conflicting values:

```
>>> df.groupby('id').filter(lambda g: (g.nunique() > 1).any())
     id  value1 value2
0  spam       1      a
3  spam       2      a
4   ham       5      x
5   ham       5      y
```

pandas.core.groupby.DataFrameGroupBy.pad

DataFrameGroupBy.**pad**(*limit=None*)

Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.pad Returns Series with minimum number of char in object.

DataFrame.pad Object with missing values filled or None if inplace=True.
Series.fillna Fill NaN values of a Series.
DataFrame.fillna Fill NaN values of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.pct_change

DataFrameGroupBy.**pct_change**(*periods=1*, *fill_method='pad'*, *limit=None*, *freq=None*, *axis=0*)

Calculate pct_change of each value to previous entry in group.

Returns

Series or DataFrame Percentage changes within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.plot

property DataFrameGroupBy.**plot**

Class implementing the .plot attribute for groupby objects.

pandas.core.groupby.DataFrameGroupBy.quantile

DataFrameGroupBy.**quantile**(*q=0.5*, *interpolation='linear'*)

Return group values at the given quantile, a la numpy.percentile.

Parameters

q [float or array-like, default 0.5 (50% quantile)] Value(s) between 0 and 1 providing the quantile(s) to compute.

interpolation [{'linear', 'lower', 'higher', 'midpoint', 'nearest'}] Method to use when the desired quantile falls between two points.

Returns

Series or DataFrame Return type determined by caller of GroupBy object.

See also:

Series.quantile Similar method for Series.
DataFrame.quantile Similar method for DataFrame.
numpy.percentile NumPy method to compute qth percentile.

Examples

```
>>> df = pd.DataFrame([
...     ['a', 1], ['a', 2], ['a', 3],
...     ['b', 1], ['b', 3], ['b', 5]
... ], columns=['key', 'val'])
>>> df.groupby('key').quantile()
    val
key
a    2.0
b    3.0
```

pandas.core.groupby.DataFrameGroupBy.rank

DataFrameGroupBy.**rank**(*method='average'*, *ascending=True*, *na_option='keep'*, *pct=False*, *axis=0*)

Provide the rank of values within each group.

Parameters

method [{'average', 'min', 'max', 'first', 'dense'}, default 'average']

- average: average rank of group.
- min: lowest rank in group.
- max: highest rank in group.
- first: ranks assigned in order they appear in the array.
- dense: like 'min', but rank always increases by 1 between groups.

ascending [bool, default True] False for ranks by high (1) to low (N).

na_option [{'keep', 'top', 'bottom'}, default 'keep']

- keep: leave NA values where they are.
- top: smallest rank if ascending.
- bottom: smallest rank if descending.

pct [bool, default False] Compute percentage rank of data within each group.

axis [int, default 0] The axis of the object over which to compute the rank.

Returns

DataFrame with ranking of values within each group

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.resample

DataFrameGroupBy.**resample**(*rule*, **args*, ***kwargs*)

Provide resampling when using a TimeGrouper.

Given a grouper, the function resamples it according to a string "string" -> "frequency".

See the *frequency aliases* documentation for more details.

Parameters

rule [str or DateOffset] The offset string or object representing target grouper conversion.

***args, **kwargs** Possible arguments are *how*, *fill_method*, *limit*, *kind* and *on*, and other arguments of *TimeGrouper*.

Returns

Grouper Return a new grouper with our resampler appended.

See also:

Grouper Specify a frequency to resample with when grouping by a key.
DatetimeIndex.resample Frequency conversion and resampling of time series.

Examples

```
>>> idx = pd.date_range('1/1/2000', periods=4, freq='T')
>>> df = pd.DataFrame(data=4 * [range(2)],
...                   index=idx,
...                   columns=['a', 'b'])
>>> df.iloc[2, 0] = 5
>>> df
                     a  b
2000-01-01 00:00:00  0  1
2000-01-01 00:01:00  0  1
2000-01-01 00:02:00  5  1
2000-01-01 00:03:00  0  1
```

Downsample the DataFrame into 3 minute bins and sum the values of the timestamps falling into a bin.

```
>>> df.groupby('a').resample('3T').sum()
                          a  b
a
0   2000-01-01 00:00:00  0  2
    2000-01-01 00:03:00  0  1
5   2000-01-01 00:00:00  5  1
```

Upsample the series into 30 second bins.

```
>>> df.groupby('a').resample('30S').sum()
                     a  b
a
0   2000-01-01 00:00:00  0  1
    2000-01-01 00:00:30  0  0
    2000-01-01 00:01:00  0  1
    2000-01-01 00:01:30  0  0
    2000-01-01 00:02:00  0  0
    2000-01-01 00:02:30  0  0
    2000-01-01 00:03:00  0  1
5   2000-01-01 00:02:00  5  1
```

Resample by month. Values are assigned to the month of the period.

```
>>> df.groupby('a').resample('M').sum()
            a  b
a
0   2000-01-31  0  3
5   2000-01-31  5  1
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```
>>> df.groupby('a').resample('3T', closed='right').sum()
                          a  b
a
0   1999-12-31 23:57:00  0  1
    2000-01-01 00:00:00  0  2
5   2000-01-01 00:00:00  5  1
```

Downsample the series into 3 minute bins and close the right side of the bin interval, but label each bin using the right edge instead of the left.

```
>>> df.groupby('a').resample('3T', closed='right', label='right').sum()
                         a  b
a
0   2000-01-01 00:00:00  0  1
    2000-01-01 00:03:00  0  2
5   2000-01-01 00:03:00  5  1
```

pandas.core.groupby.DataFrameGroupBy.sample

DataFrameGroupBy.**sample**(*n=None*, *frac=None*, *replace=False*, *weights=None*, *random_state=None*)

Return a random sample of items from each group.

You can use *random_state* for reproducibility.

New in version 1.1.0.

Parameters

n [int, optional] Number of items to return for each group. Cannot be used with *frac* and must be no larger than the smallest group unless *replace* is True. Default is one if *frac* is None.

frac [float, optional] Fraction of items to return. Cannot be used with *n*.

replace [bool, default False] Allow or disallow sampling of the same row more than once.

weights [list-like, optional] Default None results in equal probability weighting. If passed a list-like then values must have the same length as the underlying DataFrame or Series object and will be used as sampling probabilities after normalization within each group. Values must be non-negative with at least one positive element within each group.

random_state [int, array-like, BitGenerator, np.random.RandomState, optional] If int, array-like, or BitGenerator (NumPy>=1.17), seed for random number generator If np.random.RandomState, use as numpy RandomState object.

Returns

Series or DataFrame A new object of same type as caller containing items randomly sampled within each group from the caller object.

See also:

DataFrame.sample Generate random samples from a DataFrame object.
numpy.random.choice Generate a random sample from a given 1-D numpy array.

Examples

```
>>> df = pd.DataFrame(
...     {"a": ["red"] * 2 + ["blue"] * 2 + ["black"] * 2, "b": range(6)}
... )
>>> df
       a  b
0    red  0
1    red  1
2   blue  2
3   blue  3
4  black  4
5  black  5
```

Select one row at random for each distinct value in column a. The *random_state* argument can be used to guarantee reproducibility:

```
>>> df.groupby("a").sample(n=1, random_state=1)
       a  b
4  black  4
2   blue  2
1    red  1
```

Set *frac* to sample fixed proportions rather than counts:

```
>>> df.groupby("a")["b"].sample(frac=0.5, random_state=2)
5    5
2    2
0    0
Name: b, dtype: int64
```

Control sample probabilities within groups by setting weights:

```
>>> df.groupby("a").sample(
...     n=1,
...     weights=[1, 1, 1, 0, 0, 1],
...     random_state=1,
... )
       a  b
5  black  5
2   blue  2
0    red  0
```

pandas.core.groupby.DataFrameGroupBy.shift

DataFrameGroupBy.**shift**(*periods=1*, *freq=None*, *axis=0*, *fill_value=None*)

Shift each group by periods observations.

If freq is passed, the index will be increased using the periods and the freq.

Parameters

periods [int, default 1] Number of periods to shift.

freq [str, optional] Frequency string.

axis [axis to shift, default 0] Shift direction.

fill_value [optional] The scalar value to use for newly introduced missing values.

New in version 0.24.0.

Returns

Series or DataFrame Object shifted within each group.

See also:

Index.shift Shift values of Index.

tshift Shift the time index, using the index's frequency if available.

pandas.core.groupby.DataFrameGroupBy.size

DataFrameGroupBy.**size**()

Compute group sizes.

Returns

DataFrame or Series Number of rows in each group as a Series if as_index is True or a DataFrame if as_index is False.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.groupby.DataFrameGroupBy.skew

property DataFrameGroupBy.**skew**

Return unbiased skew over requested axis.

Normalized by N-1.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

****kwargs** Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.take

property DataFrameGroupBy.**take**

Return the elements in the given *positional* indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

Parameters

indices [array-like] An array of ints indicating which positions to take.

axis [{0 or 'index', 1 or 'columns', None}, default 0] The axis on which to select elements. `0` means that we are selecting rows, `1` means that we are selecting columns.

is_copy [bool] Before pandas 1.0, `is_copy=False` can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, `take` always returns a copy, and the keyword is therefore deprecated.

Deprecated since version 1.0.0.

****kwargs** For compatibility with `numpy.take()`. Has no effect on the output.

Returns

taken [same type as caller] An array-like containing the elements taken from the object.

See also:

`DataFrame.loc` Select a subset of a DataFrame by labels.
`DataFrame.iloc` Select a subset of a DataFrame by positions.
`numpy.take` Take elements from an array along an axis.

Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                    ('parrot', 'bird', 24.0),
...                    ('lion', 'mammal', 80.5),
...                    ('monkey', 'mammal', np.nan)],
...                   columns=['name', 'class', 'max_speed'],
...                   index=[0, 2, 3, 1])
>>> df
     name   class  max_speed
0  falcon    bird      389.0
2  parrot    bird       24.0
3    lion  mammal       80.5
1  monkey  mammal        NaN
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```
>>> df.take([0, 3])
     name   class  max_speed
0  falcon    bird      389.0
1  monkey  mammal        NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```
>>> df.take([1, 2], axis=1)
    class  max_speed
0    bird      389.0
2    bird       24.0
3  mammal       80.5
1  mammal        NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```
>>> df.take([-1, -2])
     name   class  max_speed
1  monkey  mammal        NaN
3    lion  mammal       80.5
```

pandas.core.groupby.DataFrameGroupBy.tshift

property DataFrameGroupBy.**tshift**

Shift the time index, using the index's frequency if available.

Deprecated since version 1.1.0: Use *shift* instead.

Parameters

periods [int] Number of periods to move, can be positive or negative.

freq [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. 'EOM').

axis [{0 or 'index', 1 or 'columns', None}, default 0] Corresponds to the axis that contains the Index.

Returns

shifted [Series/DataFrame]

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

The following methods are available only for SeriesGroupBy objects.

SeriesGroupBy.hist	Draw histogram of the input series using matplotlib.
SeriesGroupBy.nlargest	Return the largest *n* elements.
SeriesGroupBy.nsmallest	Return the smallest *n* elements.
SeriesGroupBy.nunique([dropna])	Return number of unique elements in the group.
SeriesGroupBy.unique	Return unique values of Series object.
SeriesGroupBy.value_counts([normalize, ...])	
SeriesGroupBy.is_monotonic_increasing	Alias for is_monotonic.
SeriesGroupBy.is_monotonic_decreasing	Return boolean if values in the object are monotonic_decreasing.

pandas.core.groupby.SeriesGroupBy.hist

property SeriesGroupBy.**hist**

Draw histogram of the input series using matplotlib.

Parameters

by [object, optional] If passed, then used to form histograms for separate groups.

ax [matplotlib axis object] If not passed, uses gca().

grid [bool, default True] Whether to show axis grid lines.

xlabelsize [int, default None] If specified changes the x-axis label size.

xrot [float, default None] Rotation of x axis labels.

ylabelsize [int, default None] If specified changes the y-axis label size.

yrot [float, default None] Rotation of y axis labels.

figsize [tuple, default None] Figure size in inches by default.

bins [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

legend [bool, default False] Whether to show the legend.

New in version 1.1.0.

****kwargs** To be passed to the actual plotting function.

Returns

matplotlib.AxesSubplot A histogram plot.

See also:

matplotlib.axes.Axes.hist Plot a histogram using matplotlib.

pandas.core.groupby.SeriesGroupBy.nlargest

property SeriesGroupBy.**nlargest**

Return the largest *n* elements.

Parameters

n [int, default 5] Return this many descending sorted values.

keep [{'first', 'last', 'all'}, default 'first'] When there are duplicate values that cannot all fit in a Series of *n* elements:

- **first** [return the first *n* occurrences in order] of appearance.
- **last** [return the last *n* occurrences in reverse] order of appearance.
- **all** [keep all occurrences. This can result in a Series of] size larger than *n*.

Returns

Series The *n* largest values in the Series, sorted in decreasing order.

See also:

Series.nsmallest Get the *n* smallest elements.
Series.sort_values Sort Series by values.
Series.head Return the first *n* rows.

Notes

Faster than `.sort_values(ascending=False).head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,
...                         "Malta": 434000, "Maldives": 434000,
...                         "Brunei": 434000, "Iceland": 337000,
...                         "Nauru": 11300, "Tuvalu": 11300,
...                         "Anguilla": 11300, "Montserrat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy       59000000
France      65000000
Malta         434000
Maldives      434000
Brunei        434000
Iceland       337000
Nauru          11300
Tuvalu         11300
Anguilla       11300
Montserrat      5200
dtype: int64
```

The *n* largest elements where `n=5` by default.

```
>>> s.nlargest()
France      65000000
Italy       59000000
Malta         434000
Maldives      434000
Brunei        434000
dtype: int64
```

The *n* largest elements where `n=3`. Default *keep* value is 'first' so Malta will be kept.

```
>>> s.nlargest(3)
France    65000000
Italy     59000000
Malta       434000
dtype: int64
```

The *n* largest elements where `n=3` and keeping the last duplicates. Brunei will be kept since it is the last with value 434000 based on the index order.

```
>>> s.nlargest(3, keep='last')
France      65000000
Italy       59000000
Brunei        434000
dtype: int64
```

The *n* largest elements where `n=3` with all duplicates kept. Note that the returned Series has five elements due to the three duplicates.

```
>>> s.nlargest(3, keep='all')
France      65000000
Italy       59000000
Malta         434000
Maldives      434000
Brunei        434000
dtype: int64
```

pandas.core.groupby.SeriesGroupBy.nsmallest

property SeriesGroupBy.**nsmallest**

Return the smallest *n* elements.

Parameters

n [int, default 5] Return this many ascending sorted values.

keep [{'first', 'last', 'all'}, default 'first'] When there are duplicate values that cannot all fit in a Series of *n* elements:

- **first** [return the first *n* occurrences in order] of appearance.
- **last** [return the last *n* occurrences in reverse] order of appearance.
- **all** [keep all occurrences. This can result in a Series of] size larger than *n*.

Returns

Series The *n* smallest values in the Series, sorted in increasing order.

See also:

Series.nlargest Get the *n* largest elements.
Series.sort_values Sort Series by values.
Series.head Return the first *n* rows.

Notes

Faster than `.sort_values().head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,
...                         "Brunei": 434000, "Malta": 434000,
...                         "Maldives": 434000, "Iceland": 337000,
...                         "Nauru": 11300, "Tuvalu": 11300,
...                         "Anguilla": 11300, "Montserrat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy       59000000
France      65000000
Brunei        434000
Malta         434000
Maldives      434000
Iceland       337000
Nauru          11300
Tuvalu         11300
Anguilla       11300
```

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```
Montserrat      5200
dtype: int64
```

The *n* smallest elements where `n=5` by default.

```
>>> s.nsmallest()
Montserrat    5200
Nauru        11300
Tuvalu       11300
Anguilla     11300
Iceland     337000
dtype: int64
```

The *n* smallest elements where `n=3`. Default *keep* value is 'first' so Nauru and Tuvalu will be kept.

```
>>> s.nsmallest(3)
Montserrat   5200
Nauru       11300
Tuvalu      11300
dtype: int64
```

The *n* smallest elements where `n=3` and keeping the last duplicates. Anguilla and Tuvalu will be kept since they are the last with value 11300 based on the index order.

```
>>> s.nsmallest(3, keep='last')
Montserrat   5200
Anguilla    11300
Tuvalu      11300
dtype: int64
```

The *n* smallest elements where `n=3` with all duplicates kept. Note that the returned Series has four elements due to the three duplicates.

```
>>> s.nsmallest(3, keep='all')
Montserrat   5200
Nauru       11300
Tuvalu      11300
Anguilla    11300
dtype: int64
```

pandas.core.groupby.SeriesGroupBy.nunique

`SeriesGroupBy.`**`nunique`**(*dropna=True*)

Return number of unique elements in the group.

Returns

Series Number of unique values within each group.

pandas.core.groupby.SeriesGroupBy.unique

property SeriesGroupBy.**unique**

Return unique values of Series object.

Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

Returns

ndarray or ExtensionArray The unique values returned as a NumPy array. See Notes.

See also:

unique Top-level unique method for any 1-d array-like object.

Index.unique Return Index with unique values from an Index object.

Notes

Returns the unique values as a NumPy array. In case of an extension-array backed Series, a new ExtensionArray of that type with just the unique values is returned. This includes

- Categorical
- Period
- Datetime with Timezone
- Interval
- Sparse
- IntegerNA

See Examples section.

Examples

```
>>> pd.Series([2, 1, 3, 3], name='A').unique()
array([2, 1, 3])
```

```
>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern')
...             for _ in range(3)]).unique()
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]
```

An unordered Categorical will return categories in the order of appearance.

```
>>> pd.Series(pd.Categorical(list('baabc'))).unique()
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```

An ordered Categorical preserves the category ordering.

```
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'),
...                          ordered=True)).unique()
['b', 'a', 'c']
Categories (3, object): ['a' < 'b' < 'c']
```

pandas.core.groupby.SeriesGroupBy.value_counts

SeriesGroupBy.**value_counts**(*normalize=False*, *sort=True*, *ascending=False*, *bins=None*, *dropna=True*)

pandas.core.groupby.SeriesGroupBy.is_monotonic_increasing

property SeriesGroupBy.**is_monotonic_increasing**

Alias for is_monotonic.

pandas.core.groupby.SeriesGroupBy.is_monotonic_decreasing

property SeriesGroupBy.**is_monotonic_decreasing**

Return boolean if values in the object are monotonic_decreasing.

Returns

bool

The following methods are available only for DataFrameGroupBy objects.

DataFrameGroupBy.corrwith	Compute pairwise correlation.
DataFrameGroupBy.boxplot([subplots, column, ...])	Make box plots from DataFrameGroupBy data.

pandas.core.groupby.DataFrameGroupBy.corrwith

property DataFrameGroupBy.**corrwith**

Compute pairwise correlation.

Pairwise correlation is computed between rows or columns of DataFrame with rows or columns of Series or DataFrame. DataFrames are first aligned along both axes before computing the correlations.

Parameters

other [DataFrame, Series] Object with which to compute correlations.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' to compute column-wise, 1 or 'columns' for row-wise.

drop [bool, default False] Drop missing indices from result.

method [{'pearson', 'kendall', 'spearman'} or callable] Method of correlation:

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- **callable: callable with input two 1d ndarrays** and returning a float.

New in version 0.24.0.

Returns

Series Pairwise correlations.

See also:

DataFrame.corr Compute pairwise correlation of columns.

pandas.core.groupby.DataFrameGroupBy.boxplot

DataFrameGroupBy.**boxplot**(*subplots=True*, *column=None*, *fontsize=None*, *rot=0*, *grid=True*, *ax=None*, *figsize=None*, *layout=None*, *sharex=False*, *sharey=True*, *backend=None*, ***kwargs*)

Make box plots from DataFrameGroupBy data.

Parameters

grouped [Grouped DataFrame]

subplots [bool]

- `False` - no subplots will be used
- `True` - create a subplot for each group.

column [column name or list of names, or vector] Can be any valid input to groupby.

fontsize [int or str]

rot [label rotation angle]

grid [Setting this to True will show the grid]

ax [Matplotlib axis object, default None]

figsize [A tuple (width, height) in inches]

layout [tuple (optional)] The layout of the plot: (rows, columns).

sharex [bool, default False] Whether x-axes will be shared among subplots.

sharey [bool, default True] Whether y-axes will be shared among subplots.

backend [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, 'matplotlib'. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

****kwargs** All other plotting keyword arguments to be passed to matplotlib's boxplot function.

Returns

dict of key/value = group key/DataFrame.boxplot return value

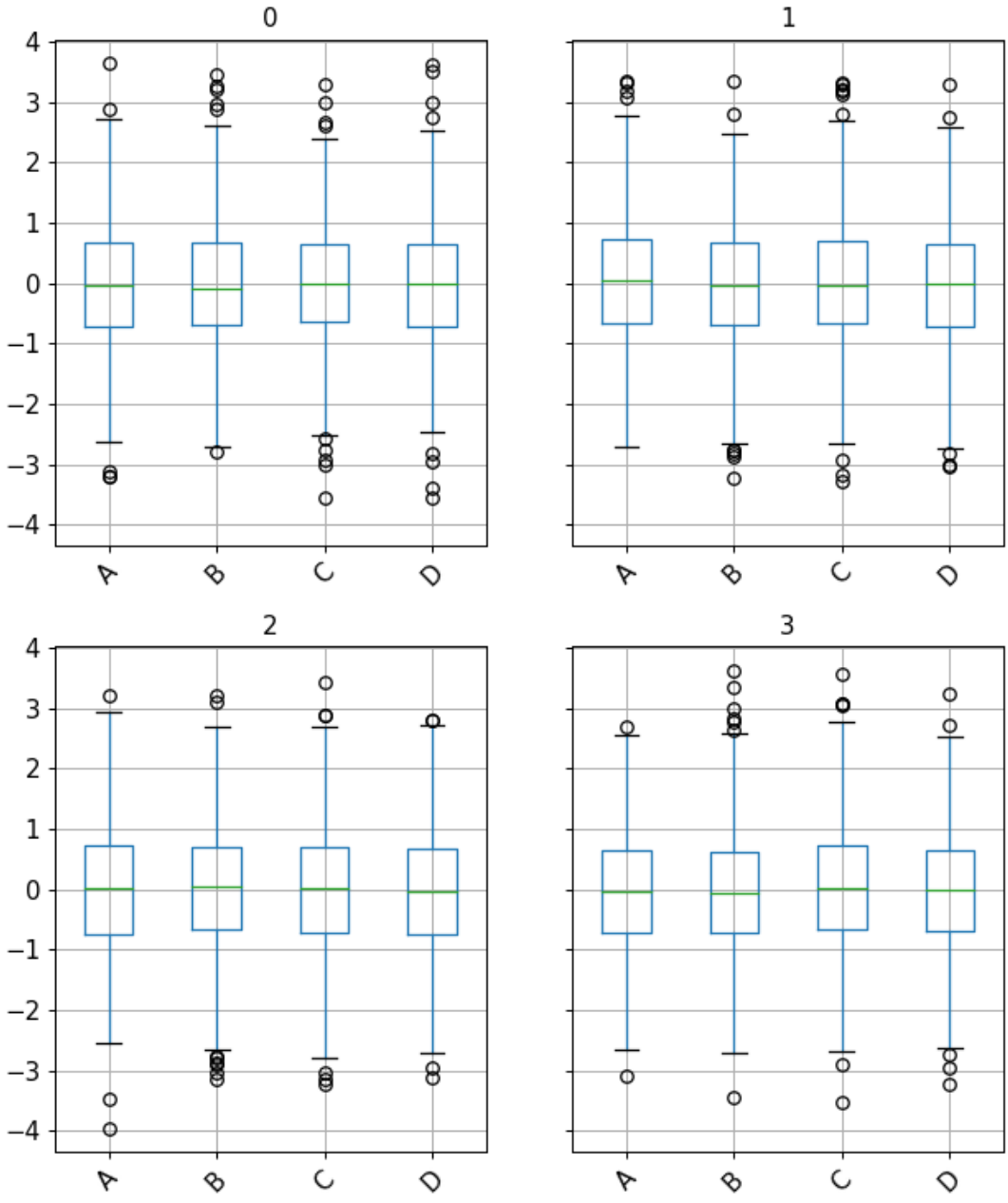
or DataFrame.boxplot return value in case subplots=figures=False

Examples

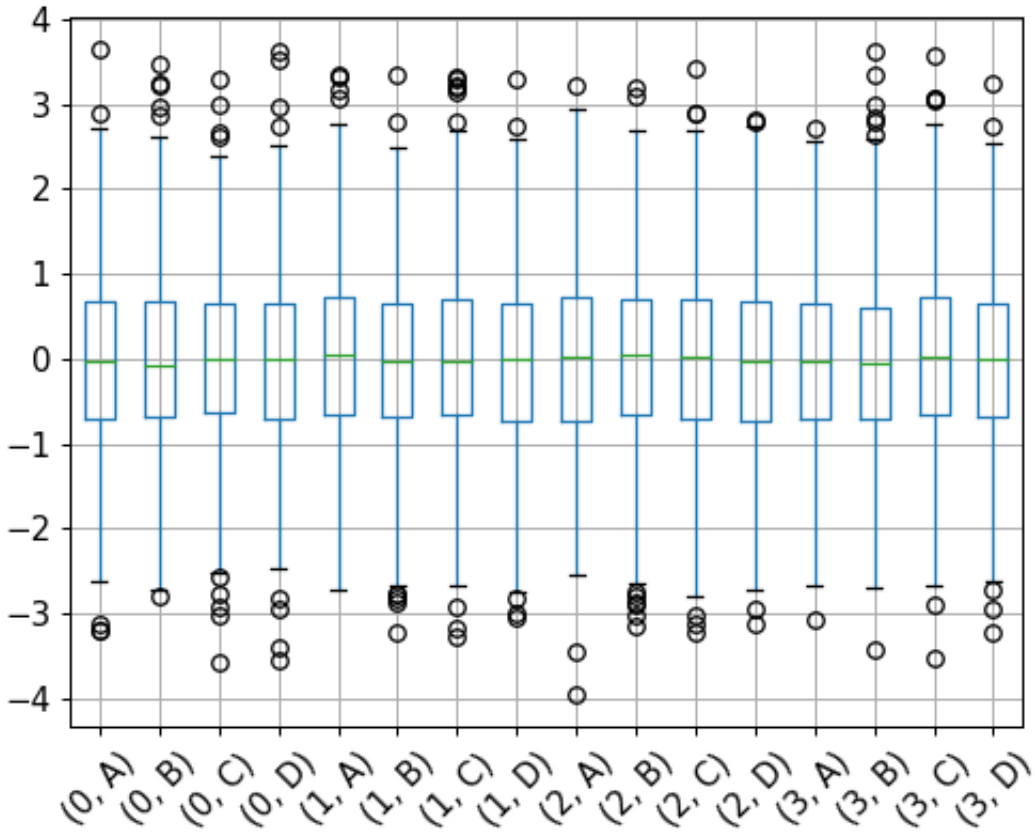
You can create boxplots for grouped data and show them as separate subplots:

```
>>> import itertools
>>> tuples = [t for t in itertools.product(range(1000), range(4))]
>>> index = pd.MultiIndex.from_tuples(tuples, names=['lvl0', 'lvl1'])
>>> data = np.random.randn(len(index),4)
>>> df = pd.DataFrame(data, columns=list('ABCD'), index=index)
>>> grouped = df.groupby(level='lvl1')
>>> grouped.boxplot(rot=45, fontsize=12, figsize=(8,10))
```

The `subplots=False` option shows the boxplots in a single figure.


0
1
2
3
4
3
2
1
0
−1
−2
−3
−4
A
B
C
D

```
>>> grouped.boxplot(subplots=False, rot=45, fontsize=12)
```



3.11 Resampling

Resampler objects are returned by resample calls: *pandas.DataFrame.resample()*, *pandas.Series.resample()*.

3.11.1 Indexing, iteration

Resampler.__iter__()	Resampler iterator.
Resampler.groups	Dict {group name -> group labels}.
Resampler.indices	Dict {group name -> group indices}.
Resampler.get_group(name[, obj])	Construct DataFrame from group with provided name.

pandas.core.resample.Resampler.__iter__

Resampler.**__iter__**()
Resampler iterator.

Returns

Generator yielding sequence of (name, subsetted object)

for each group.

See also:

GroupBy.__iter__ Generator yielding sequence for each group.

pandas.core.resample.Resampler.groups

property Resampler.**groups**
Dict {group name -> group labels}.

pandas.core.resample.Resampler.indices

property Resampler.**indices**
Dict {group name -> group indices}.

pandas.core.resample.Resampler.get_group

Resampler.**get_group**(*name*, *obj=None*)
Construct DataFrame from group with provided name.

Parameters

name [object] The name of the group to get as a DataFrame.

obj [DataFrame, default None] The DataFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used.

Returns

group [same type as obj]

3.11.2 Function application

Resampler.apply(func, *args, **kwargs)	Aggregate using one or more operations over the specified axis.
Resampler.aggregate(func, *args, **kwargs)	Aggregate using one or more operations over the specified axis.
Resampler.transform(arg, *args, **kwargs)	Call function producing a like-indexed Series on each group and return a Series with the transformed values.
Resampler.pipe(func, *args, **kwargs)	Apply a function *func* with arguments to this Resampler object and return the function's result.

pandas.core.resample.Resampler.apply

`Resampler.`**`apply`**(*func*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

`DataFrame.groupby.aggregate` Aggregate using callable, string, dict, or list of string/callables.
`DataFrame.resample.transform` Transforms the Series on each group based on the given function.
`DataFrame.aggregate` Aggregate using one or more operations over the specified axis.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> s = pd.Series([1,2,3,4,5],
                  index=pd.date_range('20130101', periods=5,freq='s'))
2013-01-01 00:00:00    1
2013-01-01 00:00:01    2
2013-01-01 00:00:02    3
2013-01-01 00:00:03    4
2013-01-01 00:00:04    5
Freq: S, dtype: int64
```

```
>>> r = s.resample('2s')
DatetimeIndexResampler [freq=<2 * Seconds>, axis=0, closed=left,
                        label=left, convention=start]
```

```
>>> r.agg(np.sum)
2013-01-01 00:00:00    3
2013-01-01 00:00:02    7
2013-01-01 00:00:04    5
Freq: 2S, dtype: int64
```

```
>>> r.agg(['sum','mean','max'])
                     sum  mean  max
2013-01-01 00:00:00    3   1.5    2
2013-01-01 00:00:02    7   3.5    4
2013-01-01 00:00:04    5   5.0    5
```

```
>>> r.agg({'result' : lambda x: x.mean() / x.std(),
           'total' : np.sum})
                     total    result
2013-01-01 00:00:00      3  2.121320
2013-01-01 00:00:02      7  4.949747
2013-01-01 00:00:04      5       NaN
```

pandas.core.resample.Resampler.aggregate

Resampler.**aggregate**(*func*, **args*, ***kwargs*)

Aggregate using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. `[np.sum, 'mean']`
- dict of axis labels -> functions, function names or list of such.

***args** Positional arguments to pass to *func*.

****kwargs** Keyword arguments to pass to *func*.

Returns

scalar, Series or DataFrame The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

DataFrame.groupby.aggregate Aggregate using callable, string, dict, or list of string/callables.
DataFrame.resample.transform Transforms the Series on each group based on the given function.
DataFrame.aggregate Aggregate using one or more operations over the specified axis.

Notes

agg is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```
>>> s = pd.Series([1,2,3,4,5],
                  index=pd.date_range('20130101', periods=5,freq='s'))
2013-01-01 00:00:00    1
2013-01-01 00:00:01    2
2013-01-01 00:00:02    3
2013-01-01 00:00:03    4
2013-01-01 00:00:04    5
Freq: S, dtype: int64
```

```
>>> r = s.resample('2s')
DatetimeIndexResampler [freq=<2 * Seconds>, axis=0, closed=left,
                        label=left, convention=start]
```

```
>>> r.agg(np.sum)
2013-01-01 00:00:00    3
2013-01-01 00:00:02    7
2013-01-01 00:00:04    5
Freq: 2S, dtype: int64
```

```
>>> r.agg(['sum','mean','max'])
                     sum  mean  max
2013-01-01 00:00:00    3   1.5    2
2013-01-01 00:00:02    7   3.5    4
2013-01-01 00:00:04    5   5.0    5
```

```
>>> r.agg({'result' : lambda x: x.mean() / x.std(),
           'total' : np.sum})
                     total    result
2013-01-01 00:00:00      3  2.121320
2013-01-01 00:00:02      7  4.949747
2013-01-01 00:00:04      5       NaN
```

pandas.core.resample.Resampler.transform

Resampler.**transform**(*arg*, **args*, ***kwargs*)

Call function producing a like-indexed Series on each group and return a Series with the transformed values.

Parameters

arg [function] To apply to each group. Should return a Series with the same index.

Returns

transformed [Series]

Examples

```
>>> resampled.transform(lambda x: (x - x.mean()) / x.std())
```

pandas.core.resample.Resampler.pipe

Resampler.**pipe**(*func*, **args*, ***kwargs*)

Apply a function *func* with arguments to this Resampler object and return the function's result.

Use *.pipe* when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing

```
>>> h(g(f(df.groupby('group')), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.groupby('group')
...    .pipe(f)
...    .pipe(g, arg1=a)
...    .pipe(h, arg2=b, arg3=c))
```

which is much more readable.

Parameters

func [callable or tuple of (callable, str)] Function to apply to this Resampler object or, alternatively, a *(callable, data_keyword)* tuple where *data_keyword* is a string indicating the keyword of *callable* that expects the Resampler object.

args [iterable, optional] Positional arguments passed into *func*.

kwargs [dict, optional] A dictionary of keyword arguments passed into *func*.

Returns

object [the return type of *func*.]

See also:

Series.pipe Apply a function with arguments to a series.
DataFrame.pipe Apply a function with arguments to a dataframe.
apply Apply function to each group instead of to the full Resampler object.

Notes

See more here

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4]},
...                   index=pd.date_range('2012-08-02', periods=4))
>>> df
            A
2012-08-02  1
2012-08-03  2
2012-08-04  3
2012-08-05  4
```

To get the difference between each 2-day period's maximum and minimum value in one pass, you can do

```
>>> df.resample('2D').pipe(lambda x: x.max() - x.min())
            A
2012-08-02  1
2012-08-04  1
```

3.11.3 Upsampling

Resampler.ffill([limit])	Forward fill the values.
Resampler.backfill([limit])	Backward fill the new missing values in the resampled data.
Resampler.bfill([limit])	Backward fill the new missing values in the resampled data.
Resampler.pad([limit])	Forward fill the values.
Resampler.nearest([limit])	Resample by using the nearest value.
Resampler.fillna(method[, limit])	Fill missing values introduced by upsampling.
Resampler.asfreq([fill_value])	Return the values at the new freq, essentially a reindex.
Resampler.interpolate([method, axis, limit, ...])	Interpolate values according to different methods.

pandas.core.resample.Resampler.ffill

Resampler.**ffill**(*limit=None*)

Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

An upsampled Series.

See also:

Series.fillna Fill NA/NaN values using the specified method.
DataFrame.fillna Fill NA/NaN values using the specified method.

pandas.core.resample.Resampler.backfill

Resampler.**backfill**(*limit=None*)

Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series, DataFrame An upsampled Series or DataFrame with backward filled NaN values.

See also:

bfill Alias of backfill.
fillna Fill NaN values using the specified method, which can be 'backfill'.
nearest Fill NaN values with nearest neighbor starting from center.
pad Forward fill NaN values.
Series.fillna Fill NaN values in the Series using the specified method, which can be 'backfill'.
DataFrame.fillna Fill NaN values in the DataFrame using the specified method, which can be 'backfill'.

References

[1]

Examples

Resampling a Series:

```
>>> s = pd.Series([1, 2, 3],
...               index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64
```

```
>>> s.resample('30min').backfill()
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```
>>> s.resample('15min').backfill(limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
2018-01-01 01:15:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 01:45:00    3.0
2018-01-01 02:00:00    3.0
Freq: 15T, dtype: float64
```

Resampling a DataFrame that has missing values:

```
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
...                   index=pd.date_range('20180101', periods=3,
...                                       freq='h'))
>>> df
                       a  b
2018-01-01 00:00:00  2.0  1
2018-01-01 01:00:00  NaN  3
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('30min').backfill()
                     a  b
2018-01-01 00:00:00  2.0  1
2018-01-01 00:30:00  NaN  3
2018-01-01 01:00:00  NaN  3
2018-01-01 01:30:00  6.0  5
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('15min').backfill(limit=2)
                     a    b
2018-01-01 00:00:00  2.0  1.0
2018-01-01 00:15:00  NaN  NaN
2018-01-01 00:30:00  NaN  3.0
2018-01-01 00:45:00  NaN  3.0
2018-01-01 01:00:00  NaN  3.0
2018-01-01 01:15:00  NaN  NaN
2018-01-01 01:30:00  6.0  5.0
2018-01-01 01:45:00  6.0  5.0
2018-01-01 02:00:00  6.0  5.0
```

pandas.core.resample.Resampler.bfill

`Resampler.`**`bfill`**(*limit=None*)

Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series, DataFrame An upsampled Series or DataFrame with backward filled NaN values.

See also:

bfill Alias of backfill.
fillna Fill NaN values using the specified method, which can be 'backfill'.
nearest Fill NaN values with nearest neighbor starting from center.
pad Forward fill NaN values.
`Series.fillna` Fill NaN values in the Series using the specified method, which can be 'backfill'.
`DataFrame.fillna` Fill NaN values in the DataFrame using the specified method, which can be 'backfill'.

References

[1]

Examples

Resampling a Series:

```
>>> s = pd.Series([1, 2, 3],
...               index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64
```

```
>>> s.resample('30min').backfill()
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```
>>> s.resample('15min').backfill(limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
2018-01-01 01:15:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 01:45:00    3.0
2018-01-01 02:00:00    3.0
Freq: 15T, dtype: float64
```

Resampling a DataFrame that has missing values:

```
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
...                   index=pd.date_range('20180101', periods=3,
...                                       freq='h'))
>>> df
                       a  b
2018-01-01 00:00:00  2.0  1
2018-01-01 01:00:00  NaN  3
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('30min').backfill()
                       a  b
2018-01-01 00:00:00  2.0  1
2018-01-01 00:30:00  NaN  3
2018-01-01 01:00:00  NaN  3
2018-01-01 01:30:00  6.0  5
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('15min').backfill(limit=2)
                       a    b
2018-01-01 00:00:00  2.0  1.0
2018-01-01 00:15:00  NaN  NaN
2018-01-01 00:30:00  NaN  3.0
```

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```
2018-01-01 00:45:00  NaN  3.0
2018-01-01 01:00:00  NaN  3.0
2018-01-01 01:15:00  NaN  NaN
2018-01-01 01:30:00  6.0  5.0
2018-01-01 01:45:00  6.0  5.0
2018-01-01 02:00:00  6.0  5.0
```

pandas.core.resample.Resampler.pad

Resampler.**pad**(*limit=None*)

Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

An upsampled Series.

See also:

Series.fillna Fill NA/NaN values using the specified method.
DataFrame.fillna Fill NA/NaN values using the specified method.

pandas.core.resample.Resampler.nearest

Resampler.**nearest**(*limit=None*)

Resample by using the nearest value.

When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The *nearest* method will replace NaN values that appeared in the resampled data with the value from the nearest member of the sequence, based on the index value. Missing values that existed in the original data will not be modified. If *limit* is given, fill only this many values in each direction for each of the original values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame An upsampled Series or DataFrame with NaN values filled with their nearest value.

See also:

backfill Backward fill the new missing values in the resampled data.
pad Forward fill NaN values.

Examples

```
>>> s = pd.Series([1, 2],
...               index=pd.date_range('20180101',
...                                   periods=2,
...                                   freq='1h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
Freq: H, dtype: int64
```

```
>>> s.resample('15min').nearest()
2018-01-01 00:00:00    1
2018-01-01 00:15:00    1
2018-01-01 00:30:00    2
2018-01-01 00:45:00    2
2018-01-01 01:00:00    2
Freq: 15T, dtype: int64
```

Limit the number of upsampled values imputed by the nearest:

```
>>> s.resample('15min').nearest(limit=1)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
Freq: 15T, dtype: float64
```

pandas.core.resample.Resampler.fillna

Resampler.**fillna**(*method*, *limit=None*)

Fill missing values introduced by upsampling.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency).

Missing values that existed in the original data will not be modified.

Parameters

method [{'pad', 'backfill', 'ffill', 'bfill', 'nearest'}] Method to use for filling holes in resampled data

- 'pad' or 'ffill': use previous valid observation to fill gap (forward fill).
- 'backfill' or 'bfill': use next valid observation to fill gap.
- 'nearest': use nearest valid observation to fill gap.

limit [int, optional] Limit of how many consecutive missing values to fill.

Returns

Series or DataFrame An upsampled Series or DataFrame with missing values filled.

See also:

backfill Backward fill NaN values in the resampled data.
pad Forward fill NaN values in the resampled data.
nearest Fill NaN values in the resampled data with nearest neighbor starting from center.

interpolate Fill NaN values using interpolation.
Series.fillna Fill NaN values in the Series using the specified method, which can be 'bfill' and 'ffill'.
DataFrame.fillna Fill NaN values in the DataFrame using the specified method, which can be 'bfill' and 'ffill'.

References

[1]

Examples

Resampling a Series:

```
>>> s = pd.Series([1, 2, 3],
...               index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64
```

Without filling the missing values you get:

```
>>> s.resample("30min").asfreq()
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 01:00:00    2.0
2018-01-01 01:30:00    NaN
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

```
>>> s.resample('30min').fillna("backfill")
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```
>>> s.resample('15min').fillna("backfill", limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
2018-01-01 01:15:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 01:45:00    3.0
2018-01-01 02:00:00    3.0
Freq: 15T, dtype: float64
```

```
>>> s.resample('30min').fillna("pad")
2018-01-01 00:00:00    1
2018-01-01 00:30:00    1
```

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```
2018-01-01 01:00:00    2
2018-01-01 01:30:00    2
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```
>>> s.resample('30min').fillna("nearest")
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

Missing values present before the upsampling are not affected.

```
>>> sm = pd.Series([1, None, 3],
...                index=pd.date_range('20180101', periods=3, freq='h'))
>>> sm
2018-01-01 00:00:00    1.0
2018-01-01 01:00:00    NaN
2018-01-01 02:00:00    3.0
Freq: H, dtype: float64
```

```
>>> sm.resample('30min').fillna('backfill')
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 01:00:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

```
>>> sm.resample('30min').fillna('pad')
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    1.0
2018-01-01 01:00:00    NaN
2018-01-01 01:30:00    NaN
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

```
>>> sm.resample('30min').fillna('nearest')
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 01:00:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

DataFrame resampling is done column-wise. All the same options are available.

```
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
...                   index=pd.date_range('20180101', periods=3,
...                                       freq='h'))
>>> df
                       a  b
2018-01-01 00:00:00  2.0  1
```

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```
2018-01-01 01:00:00  NaN  3
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('30min').fillna("bfill")
                     a  b
2018-01-01 00:00:00  2.0  1
2018-01-01 00:30:00  NaN  3
2018-01-01 01:00:00  NaN  3
2018-01-01 01:30:00  6.0  5
2018-01-01 02:00:00  6.0  5
```

pandas.core.resample.Resampler.asfreq

Resampler.**asfreq**(*fill_value=None*)

Return the values at the new freq, essentially a reindex.

Parameters

fill_value [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

Returns

DataFrame or Series Values at the specified freq.

See also:

Series.asfreq Convert TimeSeries to specified frequency.
DataFrame.asfreq Convert TimeSeries to specified frequency.

pandas.core.resample.Resampler.interpolate

Resampler.**interpolate**(*method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs*)

Interpolate values according to different methods.

Fill NaN values using an interpolation method.

Please note that only `method='linear'` is supported for DataFrame/Series with a MultiIndex.

Parameters

method [str, default 'linear'] Interpolation technique to use. One of:

- 'linear': Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
- 'time': Works on daily and higher resolution data to interpolate given length of interval.
- 'index', 'values': use the actual numerical values of the index.
- 'pad': Fill in NaNs using existing values.
- 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'spline', 'barycentric', 'polynomial': Passed to *scipy.interpolate.interp1d*. These methods use the numerical values of the index. Both 'polynomial' and 'spline' require that you also specify an *order* (int), e.g. `df.interpolate(method='polynomial', order=5)`.
- 'krogh', 'piecewise_polynomial', 'spline', 'pchip', 'akima', 'cubicspline': Wrappers around the SciPy interpolation methods of similar names. See *Notes*.

- 'from_derivatives': Refers to *scipy.interpolate.BPoly.from_derivatives* which replaces 'piecewise_polynomial' interpolation method in scipy 0.18.

axis [{{0 or 'index', 1 or 'columns', None}}, default None] Axis to interpolate along.

limit [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

inplace [bool, default False] Update the data in place if possible.

limit_direction [{{'forward', 'backward', 'both'}}, Optional] Consecutive NaNs will be filled in this direction.

If limit is specified:

- If 'method' is 'pad' or 'ffill', 'limit_direction' must be 'forward'.
- If 'method' is 'backfill' or 'bfill', 'limit_direction' must be 'backwards'.

If 'limit' is not specified:

- If 'method' is 'backfill' or 'bfill', the default is 'backward'
- else the default is 'forward'

Changed in version 1.1.0: raises ValueError if *limit_direction* is 'forward' or 'both' and method is 'backfill' or 'bfill'. raises ValueError if *limit_direction* is 'backward' or 'both' and method is 'pad' or 'ffill'.

limit_area [{{*None*, 'inside', 'outside'}}, default None] If limit is specified, consecutive NaNs will be filled with this restriction.

- `None`: No fill restriction.
- 'inside': Only fill NaNs surrounded by valid values (interpolate).
- 'outside': Only fill NaNs outside valid values (extrapolate).

downcast [optional, 'infer' or None, defaults to None] Downcast dtypes if possible.

``**kwargs`` [optional] Keyword arguments to pass on to the interpolating function.

Returns

Series or DataFrame or None Returns the same object type as the caller, interpolated at some or all `NaN` values or None if `inplace=True`.

See also:

fillna Fill missing values using different methods.
scipy.interpolate.Akima1DInterpolator Piecewise cubic polynomials (Akima interpolator).
scipy.interpolate.BPoly.from_derivatives Piecewise polynomial in the Bernstein basis.
scipy.interpolate.interp1d Interpolate a 1-D function.
scipy.interpolate.KroghInterpolator Interpolate polynomial (Krogh interpolator).
scipy.interpolate.PchipInterpolator PCHIP 1-d monotonic cubic interpolation.
scipy.interpolate.CubicSpline Cubic spline data interpolator.

Notes

The 'krogh', 'piecewise_polynomial', 'spline', 'pchip' and 'akima' methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the SciPy documentation and SciPy tutorial.

Examples

Filling in `NaN` in a *`Series`* via linear interpolation.

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0    0.0
1    1.0
2    NaN
3    3.0
dtype: float64
>>> s.interpolate()
0    0.0
1    1.0
2    2.0
3    3.0
dtype: float64
```

Filling in `NaN` in a Series by padding, but filling at most two consecutive `NaN` at a time.

```
>>> s = pd.Series([np.nan, "single_one", np.nan,
...                "fill_two_more", np.nan, np.nan, np.nan,
...                4.71, np.nan])
>>> s
0              NaN
1       single_one
2              NaN
3    fill_two_more
4              NaN
5              NaN
6              NaN
7             4.71
8              NaN
dtype: object
>>> s.interpolate(method='pad', limit=2)
0              NaN
1       single_one
2       single_one
3    fill_two_more
4    fill_two_more
5    fill_two_more
6              NaN
7             4.71
8             4.71
dtype: object
```

Filling in `NaN` in a Series via polynomial interpolation or splines: Both 'polynomial' and 'spline' methods require that you also specify an `order` (int).

```
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0    0.000000
1    2.000000
2    4.666667
3    8.000000
dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column 'a' is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column 'b' remains `NaN`, because there is no entry before it to use for interpolation.

```
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                    (np.nan, 2.0, np.nan, np.nan),
...                    (2.0, 3.0, np.nan, 9.0),
...                    (np.nan, 4.0, -4.0, 16.0)],
...                   columns=list('abcd'))
>>> df
     a    b    c     d
0  0.0  NaN -1.0   1.0
1  NaN  2.0  NaN   NaN
2  2.0  3.0  NaN   9.0
3  NaN  4.0 -4.0  16.0
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
     a    b    c     d
0  0.0  NaN -1.0   1.0
1  1.0  2.0 -2.0   5.0
2  2.0  3.0 -3.0   9.0
3  2.0  4.0 -4.0  16.0
```

Using polynomial interpolation.

```
>>> df['d'].interpolate(method='polynomial', order=2)
0     1.0
1     4.0
2     9.0
3    16.0
Name: d, dtype: float64
```

3.11.4 Computations / descriptive stats

Resampler.count()	Compute count of group, excluding missing values.
Resampler.nunique([_method])	Return number of unique elements in the group.
Resampler.first([_method, min_count])	Compute first of group values.
Resampler.last([_method, min_count])	Compute last of group values.
Resampler.max([_method, min_count])	Compute max of group values.
Resampler.mean([_method])	Compute mean of groups, excluding missing values.
Resampler.median([_method])	Compute median of groups, excluding missing values.
Resampler.min([_method, min_count])	Compute min of group values.
Resampler.ohlc([_method])	Compute open, high, low and close values of a group, excluding missing values.

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Resampler.prod([_method, min_count])	Compute prod of group values.
Resampler.size()	Compute group sizes.
Resampler.sem([_method])	Compute standard error of the mean of groups, excluding missing values.
Resampler.std([ddof])	Compute standard deviation of groups, excluding missing values.
Resampler.sum([_method, min_count])	Compute sum of group values.
Resampler.var([ddof])	Compute variance of groups, excluding missing values.
Resampler.quantile([q])	Return value at the given quantile.

pandas.core.resample.Resampler.count

Resampler.**count**()

Compute count of group, excluding missing values.

Returns

Series or DataFrame Count of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.resample.Resampler.nunique

Resampler.**nunique**(*_method='nunique'*)

Return number of unique elements in the group.

Returns

Series Number of unique values within each group.

pandas.core.resample.Resampler.first

Resampler.**first**(*_method='first'*, *min_count=0*, **args*, ***kwargs*)

Compute first of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed first of values within each group.

pandas.core.resample.Resampler.last

Resampler.**last**(*_method='last'*, *min_count=0*, **args*, ***kwargs*)

Compute last of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed last of values within each group.

pandas.core.resample.Resampler.max

Resampler.**max**(*_method='max'*, *min_count=0*, **args*, ***kwargs*)

Compute max of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed max of values within each group.

pandas.core.resample.Resampler.mean

Resampler.**mean**(*_method='mean'*, **args*, ***kwargs*)

Compute mean of groups, excluding missing values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

Returns

pandas.Series or pandas.DataFrame

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

Examples

```
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],
...                    'B': [np.nan, 2, 3, 4, 5],
...                    'C': [1, 2, 1, 1, 2]}, columns=['A', 'B', 'C'])
```

Groupby one column and return the mean of the remaining columns in each group.

```
>>> df.groupby('A').mean()
     B         C
A
1  3.0  1.333333
2  4.0  1.500000
```

Groupby two columns and return the mean of the remaining column.

```
>>> df.groupby(['A', 'B']).mean()
       C
A B
1 2.0  2
  4.0  1
2 3.0  1
  5.0  2
```

Groupby one column and return the mean of only particular column in the group.

```
>>> df.groupby('A')['B'].mean()
A
1    3.0
2    4.0
Name: B, dtype: float64
```

pandas.core.resample.Resampler.median

Resampler.**median**(*_method='median'*, **args*, ***kwargs*)

Compute median of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

Returns

Series or DataFrame Median of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.resample.Resampler.min

Resampler.**min**(*_method='min'*, *min_count=0*, **args*, ***kwargs*)

Compute min of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed min of values within each group.

pandas.core.resample.Resampler.ohlc

Resampler.**ohlc**(*_method='ohlc'*, **args*, ***kwargs*)

Compute open, high, low and close values of a group, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

Returns

DataFrame Open, high, low and close values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.resample.Resampler.prod

Resampler.**prod**(*_method='prod'*, *min_count=0*, **args*, ***kwargs*)

Compute prod of group values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed prod of values within each group.

pandas.core.resample.Resampler.size

Resampler.**size**()

Compute group sizes.

Returns

DataFrame or Series Number of rows in each group as a Series if as_index is True or a DataFrame if as_index is False.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.resample.Resampler.sem

Resampler.**sem**(*_method='sem'*, **args*, ***kwargs*)

Compute standard error of the mean of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

Parameters

ddof [int, default 1] Degrees of freedom.

Returns

Series or DataFrame Standard error of the mean of values within each group.

See also:

Series.groupby Apply a function groupby to a Series.
DataFrame.groupby Apply a function groupby to each row or column of a DataFrame.

pandas.core.resample.Resampler.std

Resampler.**std**(*ddof=1*, **args*, ***kwargs*)

Compute standard deviation of groups, excluding missing values.

Parameters

ddof [int, default 1] Degrees of freedom.

Returns

DataFrame or Series Standard deviation of values within each group.

pandas.core.resample.Resampler.sum

Resampler.**sum**(*_method='sum'*, *min_count=0*, **args*, ***kwargs*)

Compute sum of group values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed sum of values within each group.

pandas.core.resample.Resampler.var

Resampler.**var**(*ddof=1*, **args*, ***kwargs*)

Compute variance of groups, excluding missing values.

Parameters

ddof [int, default 1] Degrees of freedom.

Returns

DataFrame or Series Variance of values within each group.

pandas.core.resample.Resampler.quantile

Resampler.**quantile**(*q=0.5*, ***kwargs*)

Return value at the given quantile.

New in version 0.24.0.

Parameters

q [float or array-like, default 0.5 (50% quantile)]

Returns

DataFrame or Series Quantile of values within each group.

See also:

Series.quantile Return a series, where the index is q and the values are the quantiles.

DataFrame.quantile Return a DataFrame, where the columns are the columns of self, and the values are the quantiles.

DataFrameGroupBy.quantile Return a DataFrame, where the coulmns are groupby columns, and the values are its quantiles.

3.12 Style

`Styler` objects are returned by *pandas.DataFrame.style*.

3.12.1 Styler constructor

Styler(data[, precision, table_styles, ...])	Helps style a DataFrame or Series according to the data with HTML and CSS.
Styler.from_custom_template(searchpath, name)	Factory function for creating a subclass of `Styler`.

pandas.io.formats.style.Styler

class pandas.io.formats.style.**Styler**(*data*, *precision=None*, *table_styles=None*, *uuid=None*, *caption=None*, *table_attributes=None*, *cell_ids=True*, *na_rep=None*, *uuid_len=5*)

Helps style a DataFrame or Series according to the data with HTML and CSS.

Parameters

data [Series or DataFrame] Data to be styled - either a Series or DataFrame.

precision [int] Precision to round floats to, defaults to pd.options.display.precision.

table_styles [list-like, default None] List of {selector: (attr, value)} dicts; see Notes.

uuid [str, default None] A unique identifier to avoid CSS collisions; generated automatically.

caption [str, default None] Caption to attach to the table.

table_attributes [str, default None] Items that show up in the opening `<table>` tag in addition to automatic (by default) id.

cell_ids [bool, default True] If True, each cell will have an `id` attribute in their HTML tag. The `id` takes the form `T_<uuid>_row<num_row>_col<num_col>` where

<uuid> is the unique identifier, <num_row> is the row number and <num_col> is the column number.

na_rep [str, optional] Representation for missing values. If na_rep is None, no special formatting is applied.

New in version 1.0.0.

uuid_len [int, default 5] If uuid is not specified, the length of the uuid to randomly generate expressed in hex characters, in range [0, 32].

New in version 1.2.0.

See also:

DataFrame.style Return a Styler object containing methods for building a styled HTML representation for the DataFrame.

Notes

Most styling will be done by passing style functions into Styler.apply or Styler.applymap. Style functions should return values with strings containing CSS 'attr: value' that will be applied to the indicated cells.

If using in the Jupyter notebook, Styler has defined a _repr_html_ to automatically render itself. Otherwise call Styler.render to get the generated HTML.

CSS classes are attached to the generated HTML

- Index and Column names include index_name and level<k> where *k* is its level in a MultiIndex
- Index label cells include
  - row_heading
  - row<n> where *n* is the numeric position of the row
  - level<k> where *k* is the level in a MultiIndex
- Column label cells include * col_heading * col<n> where *n* is the numeric position of the column * level<k> where *k* is the level in a MultiIndex
- Blank cells include blank
- Data cells include data

Attributes

env	(Jinja2 jinja2.Environment)
template	(Jinja2 Template)
loader	(Jinja2 Loader)

Methods

apply(func[, axis, subset])	Apply a function column-wise, row-wise, or table-wise.
applymap(func[, subset])	Apply a function elementwise.
background_gradient([cmap, low, high, axis, ...])	Color the background in a gradient style.
bar([subset, axis, color, width, align, ...])	Draw bar chart in the cell backgrounds.

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clear()	Reset the styler, removing any previously applied styles.
export()	Export the styles to applied to the current Styler.
format(formatter[, subset, na_rep])	Format the text display value of cells.
from_custom_template(searchpath, name)	Factory function for creating a subclass of Styler.
hide_columns(subset)	Hide columns from rendering.
hide_index()	Hide any indices from rendering.
highlight_max([subset, color, axis])	Highlight the maximum by shading the background.
highlight_min([subset, color, axis])	Highlight the minimum by shading the background.
highlight_null([null_color, subset])	Shade the background null_color for missing values.
pipe(func, *args, **kwargs)	Apply func(self, *args, **kwargs), and return the result.
render(**kwargs)	Render the built up styles to HTML.
set_caption(caption)	Set the caption on a Styler.
set_na_rep(na_rep)	Set the missing data representation on a Styler.
set_precision(precision)	Set the precision used to render.
set_properties([subset])	Method to set one or more non-data dependent properties or each cell.
set_table_attributes(attributes)	Set the table attributes.
set_table_styles(table_styles[, axis, overwrite])	Set the table styles on a Styler.
set_td_classes(classes)	Add string based CSS class names to data cells that will appear within the *Styler* HTML result.
set_uuid(uuid)	Set the uuid for a Styler.
to_excel(excel_writer[, sheet_name, na_rep, ...])	Write Styler to an Excel sheet.
use(styles)	Set the styles on the current Styler.
where(cond, value[, other, subset])	Apply a function elementwise.

pandas.io.formats.style.Styler.apply

Styler.**apply**(*func*, *axis=0*, *subset=None*, ***kwargs*)

Apply a function column-wise, row-wise, or table-wise.

Updates the HTML representation with the result.

Parameters

func [function] func should take a Series or DataFrame (depending on axis), and return an object with the same shape. Must return a DataFrame with identical index and column labels when axis=None.

axis [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (axis=0 or 'index'), to each row (axis=1 or 'columns'), or to the entire DataFrame at once with axis=None.

subset [IndexSlice] A valid indexer to limit data to *before* applying the function. Consider using a pandas.IndexSlice.

****kwargs** [dict] Pass along to func.

Returns

self [Styler]

Notes

The output shape of `func` should match the input, i.e. if `x` is the input row, column, or table (depending on `axis`), then `func(x).shape == x.shape` should be true.

This is similar to `DataFrame.apply`, except that `axis=None` applies the function to the entire DataFrame at once, rather than column-wise or row-wise.

Examples

```
>>> def highlight_max(x):
...     return ['background-color: yellow' if v == x.max() else ''
                for v in x]
...
>>> df = pd.DataFrame(np.random.randn(5, 2))
>>> df.style.apply(highlight_max)
```

pandas.io.formats.style.Styler.applymap

Styler.**applymap**(*func*, *subset=None*, ***kwargs*)

Apply a function elementwise.

Updates the HTML representation with the result.

Parameters

func [function] `func` should take a scalar and return a scalar.

subset [IndexSlice] A valid indexer to limit `data` to *before* applying the function. Consider using a pandas.IndexSlice.

****kwargs** [dict] Pass along to `func`.

Returns

self [Styler]

See also:

Styler.where Updates the HTML representation with a style which is selected in accordance with the return value of a function.

pandas.io.formats.style.Styler.background_gradient

Styler.**background_gradient**(*cmap='PuBu'*, *low=0*, *high=0*, *axis=0*, *subset=None*, *text_color_threshold=0.408*, *vmin=None*, *vmax=None*)

Color the background in a gradient style.

The background color is determined according to the data in each column (optionally row). Requires matplotlib.

Parameters

cmap [str or colormap] Matplotlib colormap.

low [float] Compress the range by the low.

high [float] Compress the range by the high.

axis [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (`axis=0` or `'index'`), to each row (`axis=1` or `'columns'`), or to the entire DataFrame at once with `axis=None`.

subset [IndexSlice] A valid slice for `data` to limit the style application to.

text_color_threshold [float or int] Luminance threshold for determining text color. Facilitates text visibility across varying background colors. From 0 to 1. 0 = all text is dark colored, 1 = all text is light colored.

New in version 0.24.0.

vmin [float, optional] Minimum data value that corresponds to colormap minimum value. When None (default): the minimum value of the data will be used.

New in version 1.0.0.

vmax [float, optional] Maximum data value that corresponds to colormap maximum value. When None (default): the maximum value of the data will be used.

New in version 1.0.0.

Returns

self [Styler]

Raises

ValueError If `text_color_threshold` is not a value from 0 to 1.

Notes

Set `text_color_threshold` or tune `low` and `high` to keep the text legible by not using the entire range of the color map. The range of the data is extended by `low * (x.max() - x.min())` and `high * (x.max() - x.min())` before normalizing.

pandas.io.formats.style.Styler.bar

`Styler.`**`bar`**(*subset=None*, *axis=0*, *color='#d65f5f'*, *width=100*, *align='left'*, *vmin=None*, *vmax=None*)

Draw bar chart in the cell backgrounds.

Parameters

subset [IndexSlice, optional] A valid slice for *data* to limit the style application to.

axis [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (`axis=0` or `'index'`), to each row (`axis=1` or `'columns'`), or to the entire DataFrame at once with `axis=None`.

color [str or 2-tuple/list] If a str is passed, the color is the same for both negative and positive numbers. If 2-tuple/list is used, the first element is the color_negative and the second is the color_positive (eg: ['#d65f5f', '#5fba7d']).

width [float, default 100] A number between 0 or 100. The largest value will cover *width* percent of the cell's width.

align [{'left', 'zero',' mid'}, default 'left'] How to align the bars with the cells.

- 'left' : the min value starts at the left of the cell.
- 'zero' : a value of zero is located at the center of the cell.

- 'mid' : the center of the cell is at (max-min)/2, or if values are all negative (positive) the zero is aligned at the right (left) of the cell.

vmin [float, optional] Minimum bar value, defining the left hand limit of the bar drawing range, lower values are clipped to *vmin*. When None (default): the minimum value of the data will be used.

New in version 0.24.0.

vmax [float, optional] Maximum bar value, defining the right hand limit of the bar drawing range, higher values are clipped to *vmax*. When None (default): the maximum value of the data will be used.

New in version 0.24.0.

Returns

self [Styler]

pandas.io.formats.style.Styler.clear

`Styler.`**`clear`**`()`

Reset the styler, removing any previously applied styles.

Returns None.

pandas.io.formats.style.Styler.export

`Styler.`**`export`**`()`

Export the styles to applied to the current Styler.

Can be applied to a second style with `Styler.use`.

Returns

styles [list]

See also:

`Styler.use` Set the styles on the current Styler.

pandas.io.formats.style.Styler.format

`Styler.`**`format`**(*formatter*, *subset=None*, *na_rep=None*)

Format the text display value of cells.

Parameters

formatter [str, callable, dict or None] If `formatter` is None, the default formatter is used.

subset [IndexSlice] An argument to `DataFrame.loc` that restricts which elements `formatter` is applied to.

na_rep [str, optional] Representation for missing values. If `na_rep` is None, no special formatting is applied.

New in version 1.0.0.

Returns

self [Styler]

Notes

`formatter` is either an `a` or a dict `{column name: a}` where `a` is one of

- str: this will be wrapped in: `a.format(x)`
- callable: called with the value of an individual cell

The default display value for numeric values is the "general" (`g`) format with `pd.options.display.precision` precision.

Examples

```
>>> df = pd.DataFrame(np.random.randn(4, 2), columns=['a', 'b'])
>>> df.style.format("{:.2%}")
>>> df['c'] = ['a', 'b', 'c', 'd']
>>> df.style.format({'c': str.upper})
```

pandas.io.formats.style.Styler.from_custom_template

classmethod `Styler.`**from_custom_template**(*searchpath*, *name*)

Factory function for creating a subclass of `Styler`.

Uses a custom template and Jinja environment.

Parameters

searchpath [str or list] Path or paths of directories containing the templates.

name [str] Name of your custom template to use for rendering.

Returns

MyStyler [subclass of Styler] Has the correct `env` and `template` class attributes set.

pandas.io.formats.style.Styler.hide_columns

`Styler.`**hide_columns**(*subset*)

Hide columns from rendering.

Parameters

subset [IndexSlice] An argument to `DataFrame.loc` that identifies which columns are hidden.

Returns

self [Styler]

pandas.io.formats.style.Styler.hide_index

Styler.**hide_index**()
Hide any indices from rendering.

Returns

self [Styler]

pandas.io.formats.style.Styler.highlight_max

Styler.**highlight_max**(*subset=None*, *color='yellow'*, *axis=0*)
Highlight the maximum by shading the background.

Parameters

subset [IndexSlice, default None] A valid slice for `data` to limit the style application to.

color [str, default 'yellow']

axis [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (`axis=0` or `'index'`), to each row (`axis=1` or `'columns'`), or to the entire DataFrame at once with `axis=None`.

Returns

self [Styler]

pandas.io.formats.style.Styler.highlight_min

Styler.**highlight_min**(*subset=None*, *color='yellow'*, *axis=0*)
Highlight the minimum by shading the background.

Parameters

subset [IndexSlice, default None] A valid slice for `data` to limit the style application to.

color [str, default 'yellow']

axis [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (`axis=0` or `'index'`), to each row (`axis=1` or `'columns'`), or to the entire DataFrame at once with `axis=None`.

Returns

self [Styler]

pandas.io.formats.style.Styler.highlight_null

Styler.**highlight_null**(*null_color='red'*, *subset=None*)

Shade the background `null_color` for missing values.

Parameters

null_color [str, default 'red']

subset [label or list of labels, default None] A valid slice for `data` to limit the style application to.

New in version 1.1.0.

Returns

self [Styler]

pandas.io.formats.style.Styler.pipe

Styler.**pipe**(*func*, **args*, ***kwargs*)

Apply `func(self, *args, **kwargs)`, and return the result.

New in version 0.24.0.

Parameters

func [function] Function to apply to the Styler. Alternatively, a `(callable, keyword)` tuple where `keyword` is a string indicating the keyword of `callable` that expects the Styler.

***args** [optional] Arguments passed to *func*.

****kwargs** [optional] A dictionary of keyword arguments passed into `func`.

Returns

object [] The value returned by `func`.

See also:

DataFrame.pipe Analogous method for DataFrame.

Styler.apply Apply a function row-wise, column-wise, or table-wise to modify the dataframe's styling.

Notes

Like `DataFrame.pipe()`, this method can simplify the application of several user-defined functions to a styler. Instead of writing:

```
f(g(df.style.set_precision(3), arg1=a), arg2=b, arg3=c)
```

users can write:

```
(df.style.set_precision(3)
   .pipe(g, arg1=a)
   .pipe(f, arg2=b, arg3=c))
```

In particular, this allows users to define functions that take a styler object, along with other parameters, and return the styler after making styling changes (such as calling *Styler.apply()* or *Styler.set_properties()*). Using `.pipe`, these user-defined style "transformations" can be interleaved with calls to the built-in Styler interface.

Examples

```
>>> def format_conversion(styler):
...     return (styler.set_properties(**{'text-align': 'right'})
...                   .format({'conversion': '{:.1%}'}))
```

The user-defined `format_conversion` function above can be called within a sequence of other style modifications:

```
>>> df = pd.DataFrame({'trial': list(range(5)),
...                    'conversion': [0.75, 0.85, np.nan, 0.7, 0.72]})
>>> (df.style
...    .highlight_min(subset=['conversion'], color='yellow')
...    .pipe(format_conversion)
...    .set_caption("Results with minimum conversion highlighted."))
```

pandas.io.formats.style.Styler.render

`Styler.`**`render`**(***kwargs*)

Render the built up styles to HTML.

Parameters

****kwargs** Any additional keyword arguments are passed through to `self.template.render`. This is useful when you need to provide additional variables for a custom template.

Returns

rendered [str] The rendered HTML.

Notes

`Styler` objects have defined the `_repr_html_` method which automatically calls `self.render()` when it's the last item in a Notebook cell. When calling `Styler.render()` directly, wrap the result in `IPython.display.HTML` to view the rendered HTML in the notebook.

Pandas uses the following keys in render. Arguments passed in `**kwargs` take precedence, so think carefully if you want to override them:

- head
- cellstyle
- body
- uuid
- precision
- table_styles
- caption

- table_attributes

pandas.io.formats.style.Styler.set_caption

Styler.**set_caption**(*caption*)

Set the caption on a Styler.

Parameters

caption [str]

Returns

self [Styler]

pandas.io.formats.style.Styler.set_na_rep

Styler.**set_na_rep**(*na_rep*)

Set the missing data representation on a Styler.

New in version 1.0.0.

Parameters

na_rep [str]

Returns

self [Styler]

pandas.io.formats.style.Styler.set_precision

Styler.**set_precision**(*precision*)

Set the precision used to render.

Parameters

precision [int]

Returns

self [Styler]

pandas.io.formats.style.Styler.set_properties

Styler.**set_properties**(*subset=None*, ***kwargs*)

Method to set one or more non-data dependent properties or each cell.

Parameters

subset [IndexSlice] A valid slice for `data` to limit the style application to.

****kwargs** [dict] A dictionary of property, value pairs to be set for each cell.

Returns

self [Styler]

Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_properties(color="white", align="right")
>>> df.style.set_properties(**{'background-color': 'yellow'})
```

pandas.io.formats.style.Styler.set_table_attributes

Styler.**set_table_attributes**(*attributes*)

Set the table attributes.

These are the items that show up in the opening `<table>` tag in addition to automatic (by default) id.

Parameters

attributes [str]

Returns

self [Styler]

Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_table_attributes('class="pure-table"')
# ... <table class="pure-table"> ...
```

pandas.io.formats.style.Styler.set_table_styles

Styler.**set_table_styles**(*table_styles*, *axis=0*, *overwrite=True*)

Set the table styles on a Styler.

These are placed in a `<style>` tag before the generated HTML table.

This function can be used to style the entire table, columns, rows or specific HTML selectors.

Parameters

table_styles [list or dict] If supplying a list, each individual table_style should be a dictionary with `selector` and `props` keys. `selector` should be a CSS selector that the style will be applied to (automatically prefixed by the table's UUID) and `props` should be a list of tuples with `(attribute, value)`. If supplying a dict, the dict keys should correspond to column names or index values, depending upon the specified *axis* argument. These will be mapped to row or col CSS selectors. MultiIndex values as dict keys should be in their respective tuple form. The dict values should be a list as specified in the form with CSS selectors and props that will be applied to the specified row or column.

Changed in version 1.2.0.

axis [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (`axis=0` or `'index'`), to each row (`axis=1` or `'columns'`). Only used if *table_styles* is dict.

New in version 1.2.0.

overwrite [boolean, default True] Styles are replaced if *True*, or extended if *False*. CSS rules are preserved so most recent styles set will dominate if selectors intersect.

New in version 1.2.0.

Returns

self [Styler]

Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 4),
...                   columns=['A', 'B', 'C', 'D'])
>>> df.style.set_table_styles(
...     [{'selector': 'tr:hover',
...       'props': [('background-color', 'yellow')]}]
... )
```

Adding column styling by name

```
>>> df.style.set_table_styles({
...     'A': [{'selector': '',
...            'props': [('color', 'red')]}],
...     'B': [{'selector': 'td',
...            'props': [('color', 'blue')]}]
... }, overwrite=False)
```

Adding row styling

```
>>> df.style.set_table_styles({
...     0: [{'selector': 'td:hover',
...          'props': [('font-size', '25px')]}]
... }, axis=1, overwrite=False)
```

pandas.io.formats.style.Styler.set_td_classes

`Styler.set_td_classes(classes)`

Add string based CSS class names to data cells that will appear within the *Styler* HTML result. These classes are added within specified <*td*> elements.

Parameters

classes [DataFrame] DataFrame containing strings that will be translated to CSS classes, mapped by identical column and index values that must exist on the underlying *Styler* data. None, NaN values, and empty strings will be ignored and not affect the rendered HTML.

Returns

self [Styler]

Examples

```
>>> df = pd.DataFrame(data=[[1, 2, 3], [4, 5, 6]], columns=["A", "B", "C"])
>>> classes = pd.DataFrame([
...     ["min-val red", "", "blue"],
...     ["red", None, "blue max-val"]
... ], index=df.index, columns=df.columns)
>>> df.style.set_td_classes(classes)
```

Using *MultiIndex* columns and a *classes DataFrame* as a subset of the underlying,

```
>>> df = pd.DataFrame([[1,2],[3,4]], index=["a", "b"],
...     columns=[["level0", "level0"], ["level1a", "level1b"]])
>>> classes = pd.DataFrame(["min-val"], index=["a"],
...     columns=[["level0"],["level1a"]])
>>> df.style.set_td_classes(classes)
```

Form of the output with new additional css classes,

```
>>> df = pd.DataFrame([[1]])
>>> css = pd.DataFrame(["other-class"])
>>> s = Styler(df, uuid="_", cell_ids=False).set_td_classes(css)
>>> s.hide_index().render()
'<style  type="text/css" ></style>'
'<table id="T__" >'
'  <thead>'
'    <tr><th class="col_heading level0 col0" >0</th></tr>'
'  </thead>'
'  <tbody>'
'    <tr><td  class="data row0 col0 other-class" >1</td></tr>'
'  </tbody>'
'</table>'
```

pandas.io.formats.style.Styler.set_uuid

Styler.**set_uuid**(*uuid*)

Set the uuid for a Styler.

Parameters

uuid [str]

Returns

self [Styler]

pandas.io.formats.style.Styler.to_excel

Styler.**to_excel**(*excel_writer*, *sheet_name='Sheet1'*, *na_rep=''*, *float_format=None*, *columns=None*, *header=True*, *index=True*, *index_label=None*, *startrow=0*, *startcol=0*, *engine=None*, *merge_cells=True*, *encoding=None*, *inf_rep='inf'*, *verbose=True*, *freeze_panes=None*)

Write Styler to an Excel sheet.

To write a single Styler to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an *ExcelWriter* object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique *sheet_name*. With all data written to the file it is necessary to save the changes. Note that creating an *ExcelWriter* object with a file name that already exists will result in the contents of the existing file being erased.

Parameters

excel_writer [path-like, file-like, or ExcelWriter object] File path or existing ExcelWriter.

sheet_name [str, default 'Sheet1'] Name of sheet which will contain DataFrame.

na_rep [str, default ''] Missing data representation.

float_format [str, optional] Format string for floating point numbers. For example `float_format="%.2f"` will format 0.1234 to 0.12.

columns [sequence or list of str, optional] Columns to write.

header [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

index_label [str or sequence, optional] Column label for index column(s) if desired. If not specified, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow [int, default 0] Upper left cell row to dump data frame.

startcol [int, default 0] Upper left cell column to dump data frame.

engine [str, optional] Write engine to use, 'openpyxl' or 'xlsxwriter'. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

Deprecated since version 1.2.0: As the xlwt package is no longer maintained, the `xlwt` engine will be removed in a future version of pandas.

merge_cells [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

encoding [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep [str, default 'inf'] Representation for infinity (there is no native representation for infinity in Excel).

verbose [bool, default True] Display more information in the error logs.

freeze_panes [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

storage_options [dict, optional] Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc., if using a URL that will be parsed by `fsspec`, e.g., starting "s3://", "gcs://". An error will be raised if providing this argument with a non-fsspec URL. See the fsspec and backend storage implementation docs for the set of allowed keys and values.

New in version 1.2.0.

See also:

to_csv Write DataFrame to a comma-separated values (csv) file.

ExcelWriter Class for writing DataFrame objects into excel sheets.

read_excel Read an Excel file into a pandas DataFrame.

read_csv Read a comma-separated values (csv) file into DataFrame.

Notes

For compatibility with `to_csv()`, to_excel serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

Examples

Create, write to and save a workbook:

```
>>> df1 = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                    index=['row 1', 'row 2'],
...                    columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```
>>> df1.to_excel("output.xlsx",
...              sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:

```
>>> with pd.ExcelWriter('output.xlsx',
...                     mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the *engine* keyword (the default engine is automatically chosen depending on the file extension):

```
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

pandas.io.formats.style.Styler.use

Styler.**use**(*styles*)

Set the styles on the current Styler.

Possibly uses styles from `Styler.export`.

Parameters

styles [list] List of style functions.

Returns

self [Styler]

See also:

Styler.export Export the styles to applied to the current Styler.

pandas.io.formats.style.Styler.where

Styler.**where**(*cond*, *value*, *other=None*, *subset=None*, ***kwargs*)

Apply a function elementwise.

Updates the HTML representation with a style which is selected in accordance with the return value of a function.

Parameters

cond [callable] `cond` should take a scalar and return a boolean.

value [str] Applied when `cond` returns true.

other [str] Applied when `cond` returns false.

subset [IndexSlice] A valid indexer to limit `data` to *before* applying the function. Consider using a pandas.IndexSlice.

****kwargs** [dict] Pass along to `cond`.

Returns

self [Styler]

See also:

Styler.applymap Updates the HTML representation with the result.

3.12.2 Styler properties

Styler.env
Styler.template
Styler.loader

pandas.io.formats.style.Styler.env

```
Styler.env = <jinja2.environment.Environment object>
```

pandas.io.formats.style.Styler.template

```
Styler.template = <Template 'html.tpl'>
```

pandas.io.formats.style.Styler.loader

```
Styler.loader = <jinja2.loaders.PackageLoader object>
```

3.12.3 Style application

Styler.apply(func[, axis, subset])	Apply a function column-wise, row-wise, or table-wise.
Styler.applymap(func[, subset])	Apply a function elementwise.
Styler.where(cond, value[, other, subset])	Apply a function elementwise.
Styler.format(formatter[, subset, na_rep])	Format the text display value of cells.
Styler.set_precision(precision)	Set the precision used to render.
Styler.set_td_classes(classes)	Add string based CSS class names to data cells that will appear within the *Styler* HTML result.
Styler.set_table_styles(table_styles[, ...])	Set the table styles on a Styler.
Styler.set_table_attributes(attributes)	Set the table attributes.
Styler.set_caption(caption)	Set the caption on a Styler.
Styler.set_properties([subset])	Method to set one or more non-data dependent properties or each cell.
Styler.set_uuid(uuid)	Set the uuid for a Styler.
Styler.set_na_rep(na_rep)	Set the missing data representation on a Styler.
Styler.clear()	Reset the styler, removing any previously applied styles.
Styler.pipe(func, *args, **kwargs)	Apply `func(self, *args, **kwargs)`, and return the result.

3.12.4 Builtin styles

Styler.highlight_max([subset, color, axis])	Highlight the maximum by shading the background.
Styler.highlight_min([subset, color, axis])	Highlight the minimum by shading the background.
Styler.highlight_null([null_color, subset])	Shade the background `null_color` for missing values.
Styler.background_gradient([cmap, low, ...])	Color the background in a gradient style.
Styler.bar([subset, axis, color, width, ...])	Draw bar chart in the cell backgrounds.

3.12.5 Style export and import

Styler.render(**kwargs)	Render the built up styles to HTML.
Styler.export()	Export the styles to applied to the current Styler.
Styler.use(styles)	Set the styles on the current Styler.
Styler.to_excel(excel_writer[, sheet_name, ...])	Write Styler to an Excel sheet.

3.13 Plotting

The following functions are contained in the `pandas.plotting` module.

andrews_curves(frame, class_column[, ax, ...])	Generate a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.
autocorrelation_plot(series[, ax])	Autocorrelation plot for time series.
bootstrap_plot(series[, fig, size, samples])	Bootstrap plot on mean, median and mid-range statistics.
boxplot(data[, column, by, ax, fontsize, ...])	Make a box plot from DataFrame columns.
deregister_matplotlib_converters()	Remove pandas formatters and converters.
lag_plot(series[, lag, ax])	Lag plot for time series.
parallel_coordinates(frame, class_column[, ...])	Parallel coordinates plotting.
plot_params	Stores pandas plotting options.
radviz(frame, class_column[, ax, color, ...])	Plot a multidimensional dataset in 2D.
register_matplotlib_converters()	Register pandas formatters and converters with matplotlib.
scatter_matrix(frame[, alpha, figsize, ax, ...])	Draw a matrix of scatter plots.
table(ax, data[, rowLabels, colLabels])	Helper function to convert DataFrame and Series to matplotlib.table.

3.13.1 pandas.plotting.andrews_curves

pandas.plotting.**andrews_curves**(*frame*, *class_column*, *ax=None*, *samples=200*, *color=None*, *colormap=None*, ***kwargs*)

Generate a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.

Andrews curves have the functional form:
f(t) = x_1/sqrt(2) + x_2 sin(t) + x_3 cos(t) + x_4 sin(2t) + x_5 cos(2t) + ...
Where x coefficients correspond to the values of each dimension and t is linearly spaced between -pi and +pi. Each row of frame then corresponds to a single curve.

Parameters

frame [DataFrame] Data to be plotted, preferably normalized to (0.0, 1.0).

class_column [Name of the column containing class names]

ax [matplotlib axes object, default None]

samples [Number of points to plot in each curve]

color [list or tuple, optional] Colors to use for the different classes.

colormap [str or matplotlib colormap object, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

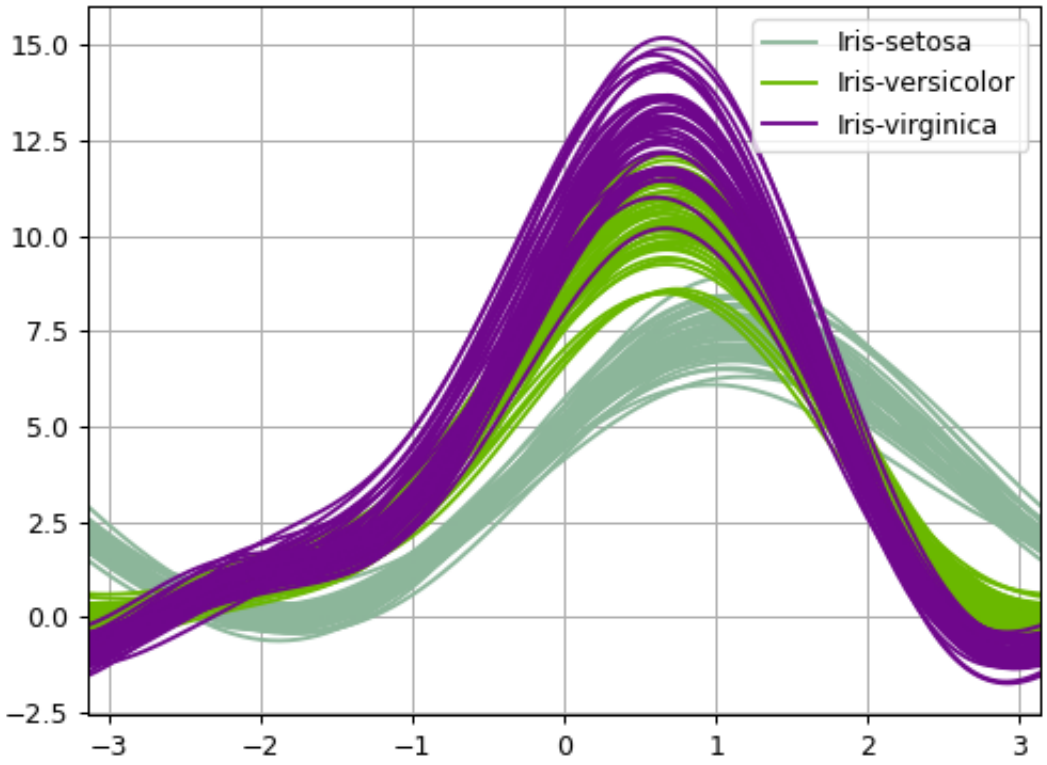
****kwargs** Options to pass to matplotlib plotting method.

Returns

class:*matplotlip.axis.Axes*

Examples

```
>>> df = pd.read_csv(
...     'https://raw.github.com/pandas-dev/'
...     'pandas/master/pandas/tests/io/data/csv/iris.csv'
... )
>>> pd.plotting.andrews_curves(df, 'Name')
```



3.13.2 pandas.plotting.autocorrelation_plot

pandas.plotting.**autocorrelation_plot**(*series*, *ax=None*, ***kwargs*)

Autocorrelation plot for time series.

Parameters

series [Time series]

ax [Matplotlib axis object, optional]

****kwargs** Options to pass to matplotlib plotting method.

Returns

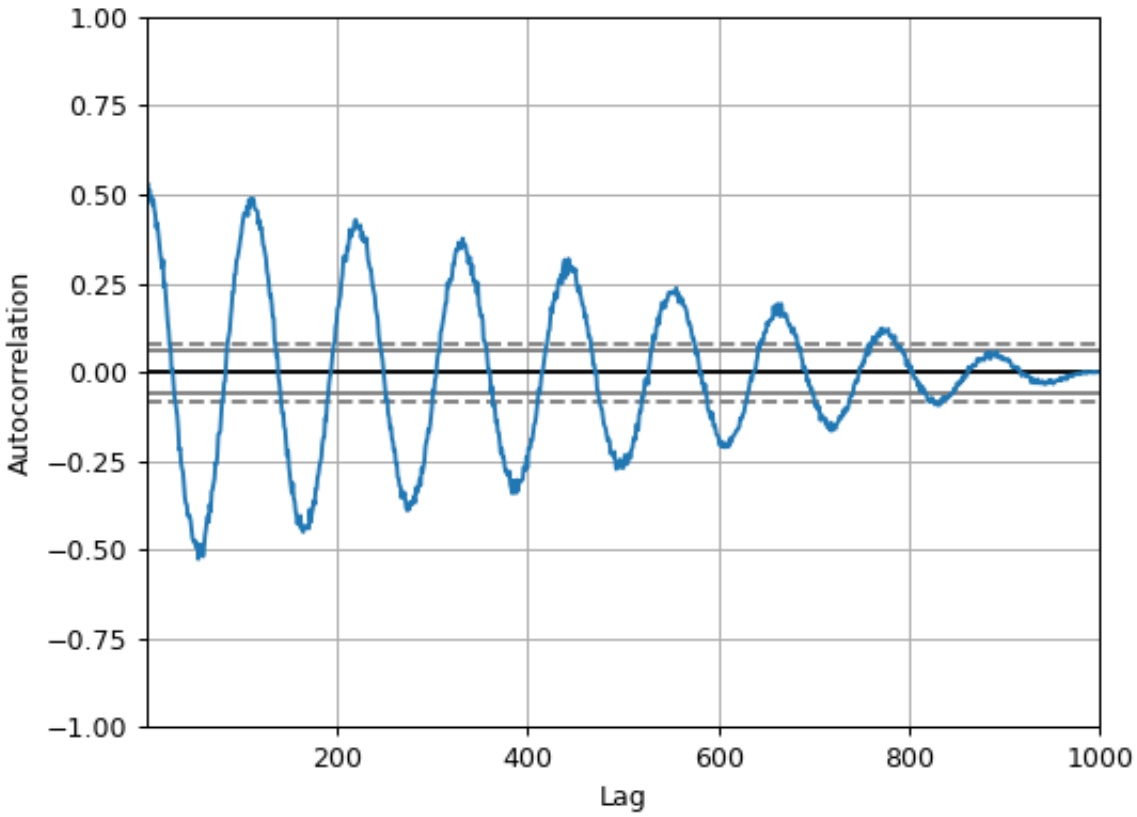
class:*matplotlib.axis.Axes*

Examples

The horizontal lines in the plot correspond to 95% and 99% confidence bands.

The dashed line is 99% confidence band.

```
>>> spacing = np.linspace(-9 * np.pi, 9 * np.pi, num=1000)
>>> s = pd.Series(0.7 * np.random.rand(1000) + 0.3 * np.sin(spacing))
>>> pd.plotting.autocorrelation_plot(s)
```



3.13.3 pandas.plotting.bootstrap_plot

pandas.plotting.**bootstrap_plot**(*series*, *fig=None*, *size=50*, *samples=500*, ***kwds*)

Bootstrap plot on mean, median and mid-range statistics.

The bootstrap plot is used to estimate the uncertainty of a statistic by relaying on random sampling with replacement [1]. This function will generate bootstrapping plots for mean, median and mid-range statistics for the given number of samples of the given size.

Parameters

series [pandas.Series] Series from where to get the samplings for the bootstrapping.

fig [matplotlib.figure.Figure, default None] If given, it will use the *fig* reference for plotting instead of creating a new one with default parameters.

size [int, default 50] Number of data points to consider during each sampling. It must be less than or equal to the length of the *series*.

samples [int, default 500] Number of times the bootstrap procedure is performed.

****kwds** Options to pass to matplotlib plotting method.

Returns

matplotlib.figure.Figure Matplotlib figure.

See also:

DataFrame.plot Basic plotting for DataFrame objects.
Series.plot Basic plotting for Series objects.

Examples

This example draws a basic bootstrap plot for a Series.

```
>>> s = pd.Series(np.random.uniform(size=100))
>>> pd.plotting.bootstrap_plot(s)
```

3.13.4 pandas.plotting.boxplot

pandas.plotting.**boxplot**(*data*, *column=None*, *by=None*, *ax=None*, *fontsize=None*, *rot=0*, *grid=True*, *figsize=None*, *layout=None*, *return_type=None*, ***kwargs*)

Make a box plot from DataFrame columns.

Make a box-and-whisker plot from DataFrame columns, optionally grouped by some other columns. A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. By default, they extend no more than *1.5 * IQR (IQR = Q3 - Q1)* from the edges of the box, ending at the farthest data point within that interval. Outliers are plotted as separate dots.

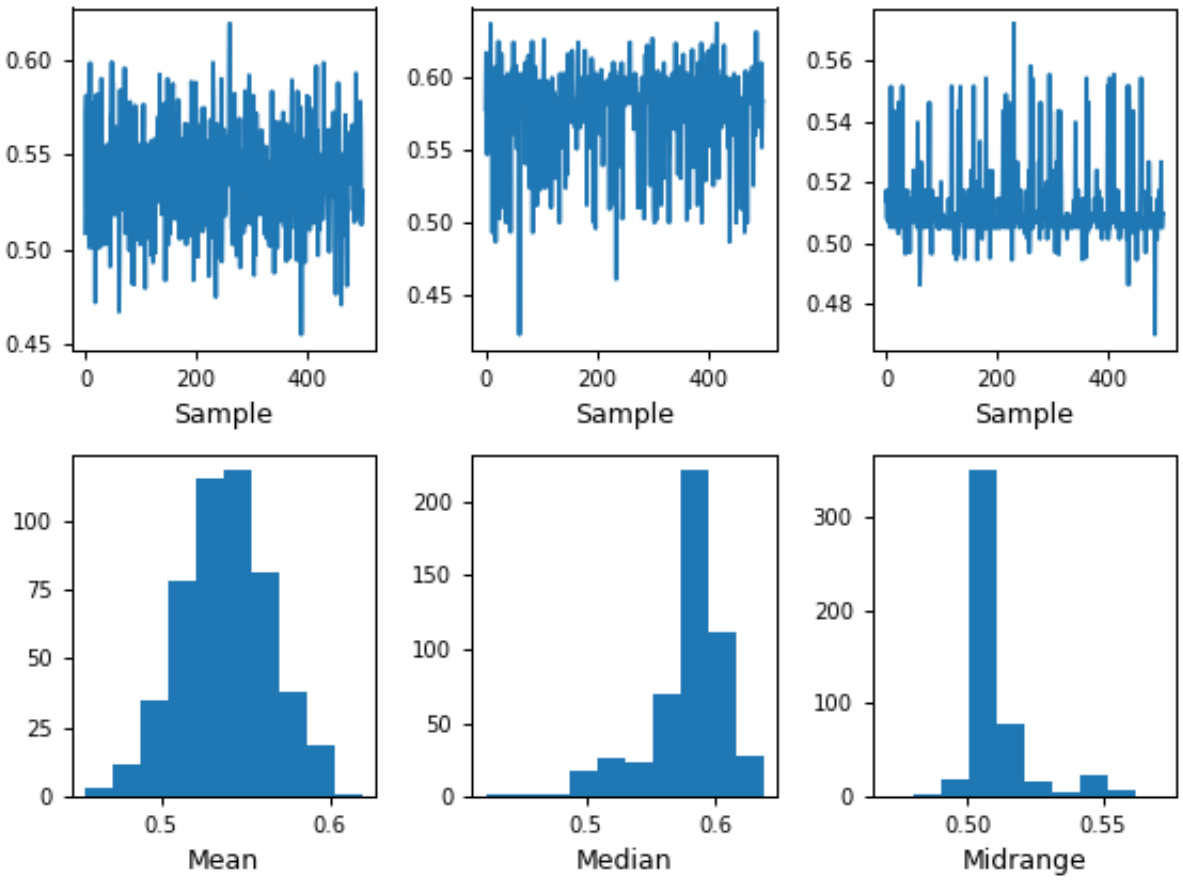
For further details see Wikipedia's entry for boxplot.

Parameters

column [str or list of str, optional] Column name or list of names, or vector. Can be any valid input to *pandas.DataFrame.groupby()*.

by [str or array-like, optional] Column in the DataFrame to *pandas.DataFrame.groupby()*. One box-plot will be done per value of columns in *by*.

ax [object of class matplotlib.axes.Axes, optional] The matplotlib axes to be used by boxplot.


0.60
0.55
0.50
0.45
0
200
400
Sample
0.60
0.55
0.50
0.45
0
200
400
Sample
0.56
0.54
0.52
0.50
0.48
0
200
400
Sample
100
75
50
25
0
0.5
0.6
Mean
200
150
100
50
0
0.5
0.6
Median
300
200
100
0
0.50
0.55
Midrange

fontsize [float or str] Tick label font size in points or as a string (e.g., *large*).

rot [int or float, default 0] The rotation angle of labels (in degrees) with respect to the screen coordinate system.

grid [bool, default True] Setting this to True will show the grid.

figsize [A tuple (width, height) in inches] The size of the figure to create in matplotlib.

layout [tuple (rows, columns), optional] For example, (3, 5) will display the subplots using 3 columns and 5 rows, starting from the top-left.

return_type [{'axes', 'dict', 'both'} or None, default 'axes'] The kind of object to return. The default is `axes`.

- 'axes' returns the matplotlib axes the boxplot is drawn on.
- 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot.
- 'both' returns a namedtuple with the axes and dict.
- when grouping with `by`, a Series mapping columns to `return_type` is returned.

  If `return_type` is *None*, a NumPy array of axes with the same shape as `layout` is returned.

****kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.boxplot()`.

Returns

result See Notes.

See also:

`Series.plot.hist` Make a histogram.
`matplotlib.pyplot.boxplot` Matplotlib equivalent plot.

Notes

The return type depends on the *return_type* parameter:
- 'axes' : object of class matplotlib.axes.Axes
- 'dict' : dict of matplotlib.lines.Line2D objects
- 'both' : a namedtuple with structure (ax, lines)

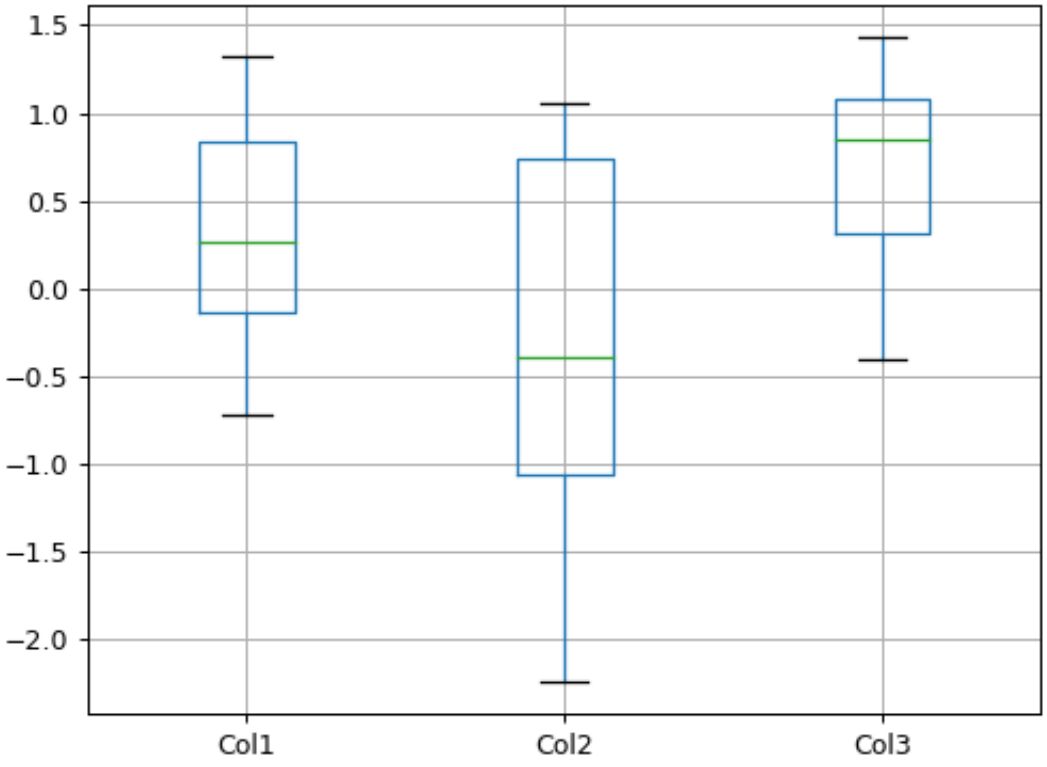
For data grouped with `by`, return a Series of the above or a numpy array:
- *Series*
- `array` (for `return_type = None`)

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

Examples

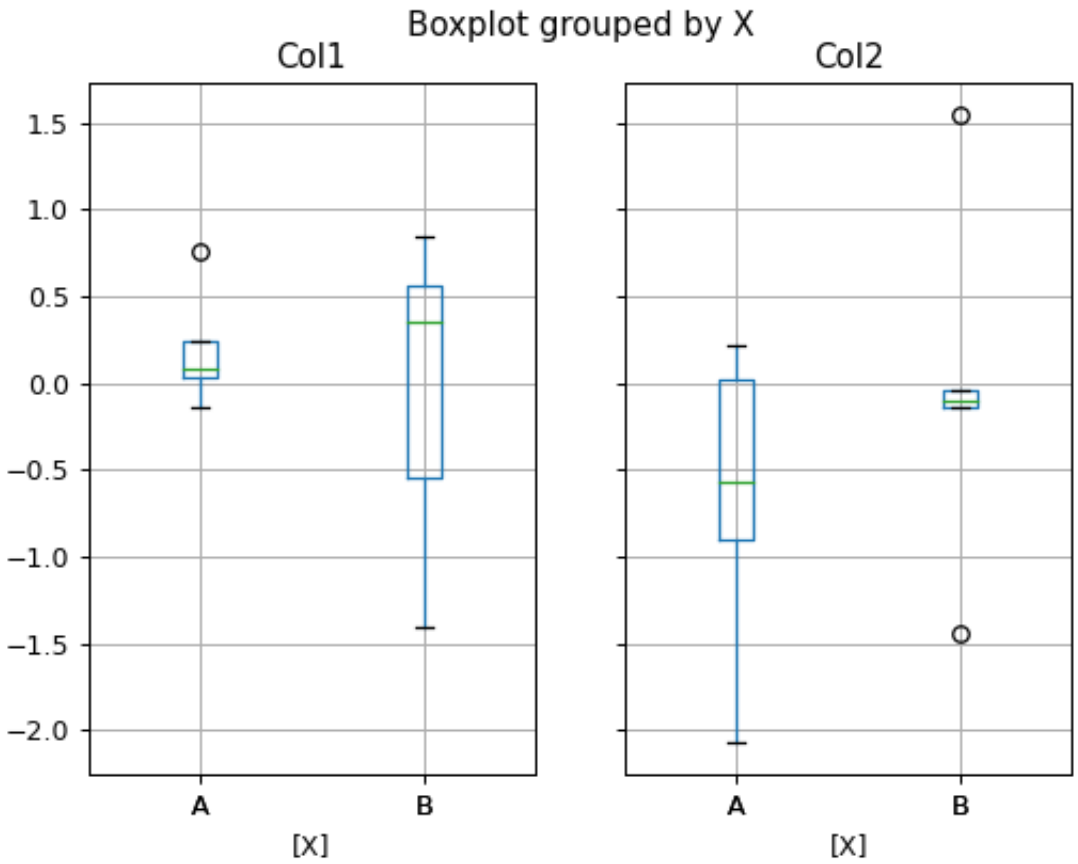
Boxplots can be created for every column in the dataframe by `df.boxplot()` or indicating the columns to be used:

```
>>> np.random.seed(1234)
>>> df = pd.DataFrame(np.random.randn(10, 4),
...                   columns=['Col1', 'Col2', 'Col3', 'Col4'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2', 'Col3'])
```


1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
Col1
Col2
Col3

Boxplots of variables distributions grouped by the values of a third variable can be created using the option `by`. For instance:

```
>>> df = pd.DataFrame(np.random.randn(10, 2),
...                   columns=['Col1', 'Col2'])
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                      'B', 'B', 'B', 'B', 'B'])
>>> boxplot = df.boxplot(by='X')
```



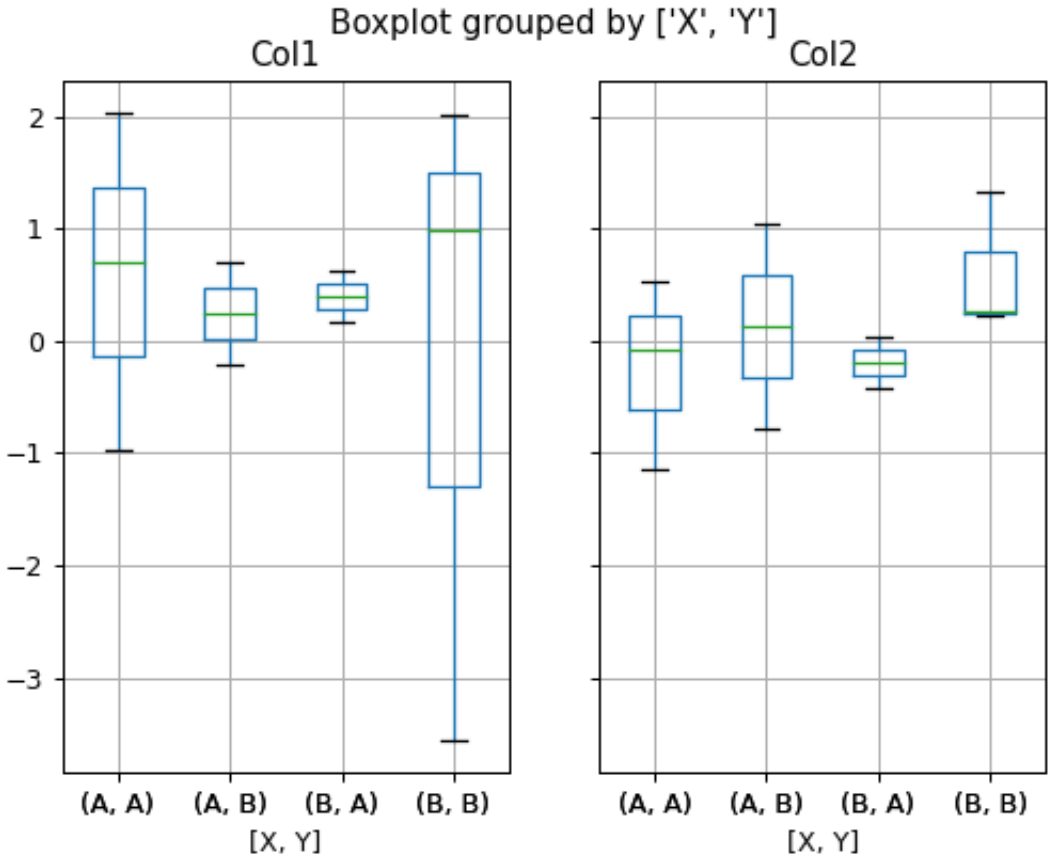
A list of strings (i.e. `['X', 'Y']`) can be passed to boxplot in order to group the data by combination of the variables in the x-axis:

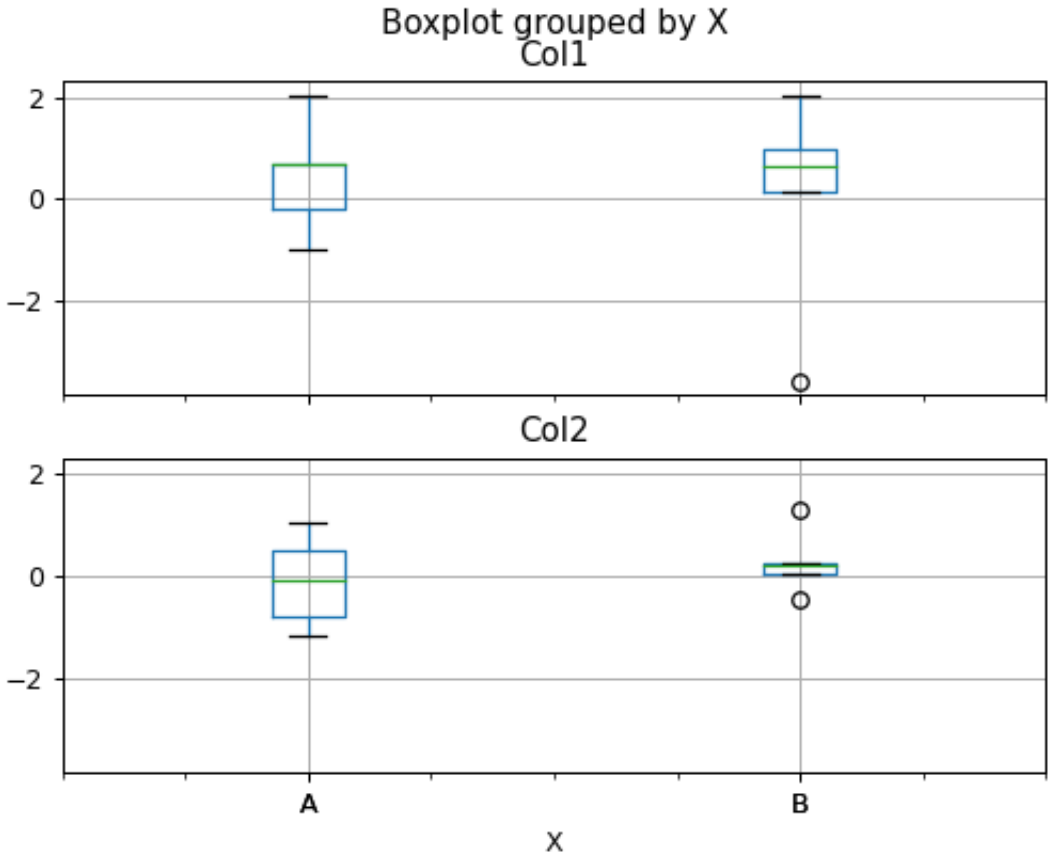
```
>>> df = pd.DataFrame(np.random.randn(10, 3),
...                   columns=['Col1', 'Col2', 'Col3'])
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                      'B', 'B', 'B', 'B', 'B'])
>>> df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A',
...                      'B', 'A', 'B', 'A', 'B'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```

The layout of boxplot can be adjusted giving a tuple to `layout`:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      layout=(2, 1))
```

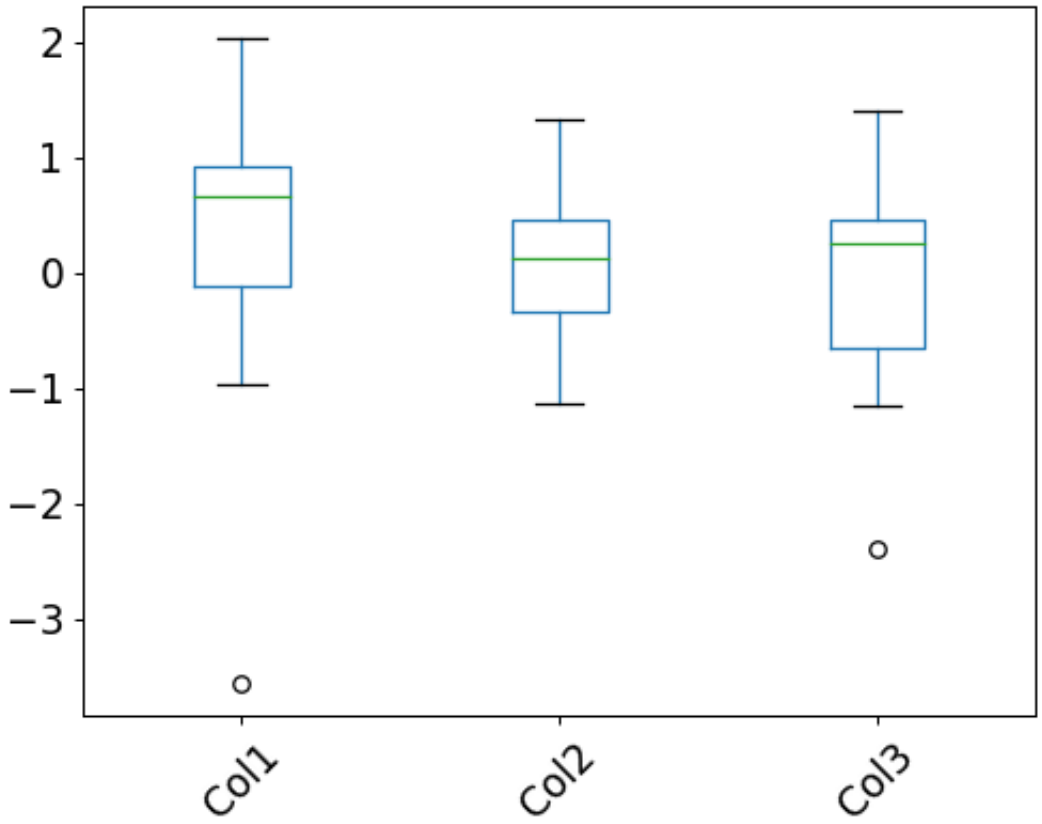
Additional formatting can be done to the boxplot, like suppressing the grid (`grid=False`), rotating the labels


Boxplot grouped by ['X', 'Y']
Col1
Col2
2
1
0
−1
−2
−3
(A, A)
(A, B)
(B, A)
(B, B)
[X, Y]
(A, A)
(A, B)
(B, A)
(B, B)
[X, Y]


Boxplot grouped by X
Col1
2
0
−2
Col2
2
0
−2
A
B
X

in the x-axis (i.e. `rot=45`) or changing the fontsize (i.e. `fontsize=15`):

```
>>> boxplot = df.boxplot(grid=False, rot=45, fontsize=15)
```



The parameter `return_type` can be used to select the type of element returned by *boxplot*. When `return_type='axes'` is selected, the matplotlib axes on which the boxplot is drawn are returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], return_type='axes')
>>> type(boxplot)
<class 'matplotlib.axes._subplots.AxesSubplot'>
```

When grouping with `by`, a Series mapping columns to `return_type` is returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      return_type='axes')
>>> type(boxplot)
<class 'pandas.core.series.Series'>
```

If `return_type` is *None*, a NumPy array of axes with the same shape as `layout` is returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      return_type=None)
>>> type(boxplot)
<class 'numpy.ndarray'>
```

3.13.5 pandas.plotting.deregister_matplotlib_converters

pandas.plotting.**deregister_matplotlib_converters**()

Remove pandas formatters and converters.

Removes the custom converters added by `register()`. This attempts to set the state of the registry back to the state before pandas registered its own units. Converters for pandas' own types like Timestamp and Period are removed completely. Converters for types pandas overwrites, like `datetime.datetime`, are restored to their original value.

See also:

register_matplotlib_converters Register pandas formatters and converters with matplotlib.

3.13.6 pandas.plotting.lag_plot

pandas.plotting.**lag_plot**(*series*, *lag=1*, *ax=None*, ***kwds*)

Lag plot for time series.

Parameters

series [Time series]

lag [lag of the scatter plot, default 1]

ax [Matplotlib axis object, optional]

****kwds** Matplotlib scatter method keyword arguments.

Returns

class:*matplotlib.axis.Axes*

Examples

Lag plots are most commonly used to look for patterns in time series data.

Given the following time series

```
>>> np.random.seed(5)
>>> x = np.cumsum(np.random.normal(loc=1, scale=5, size=50))
>>> s = pd.Series(x)
>>> s.plot()
```

A lag plot with `lag=1` returns

```
>>> pd.plotting.lag_plot(s, lag=1)
```

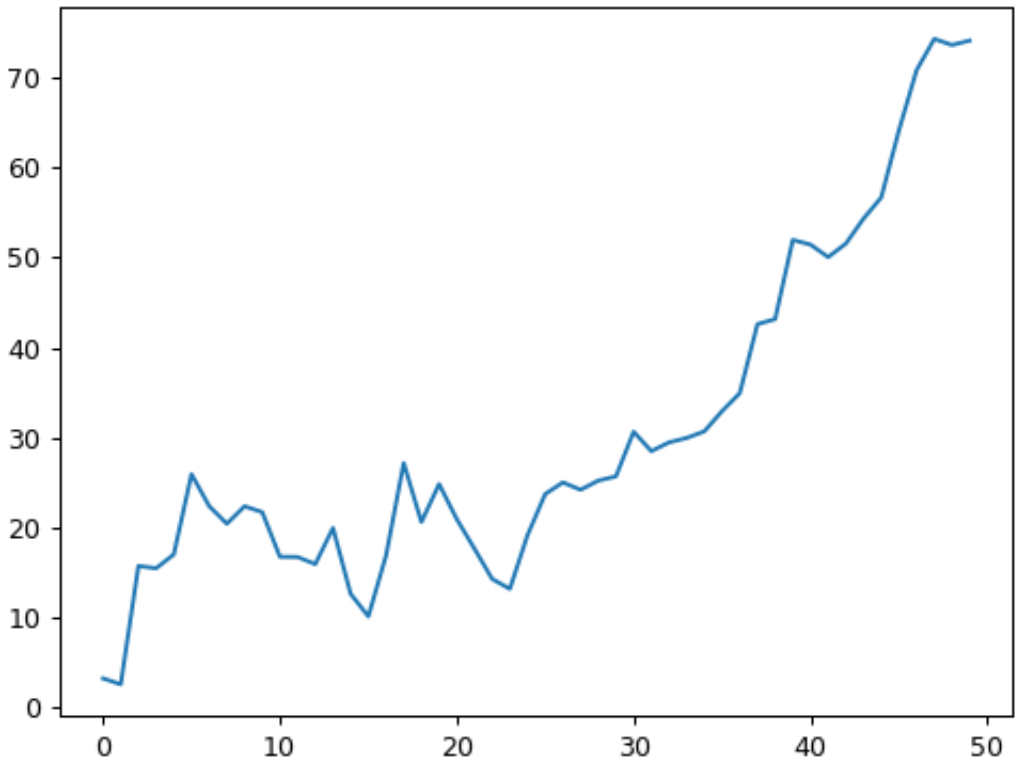
3.13.7 pandas.plotting.parallel_coordinates

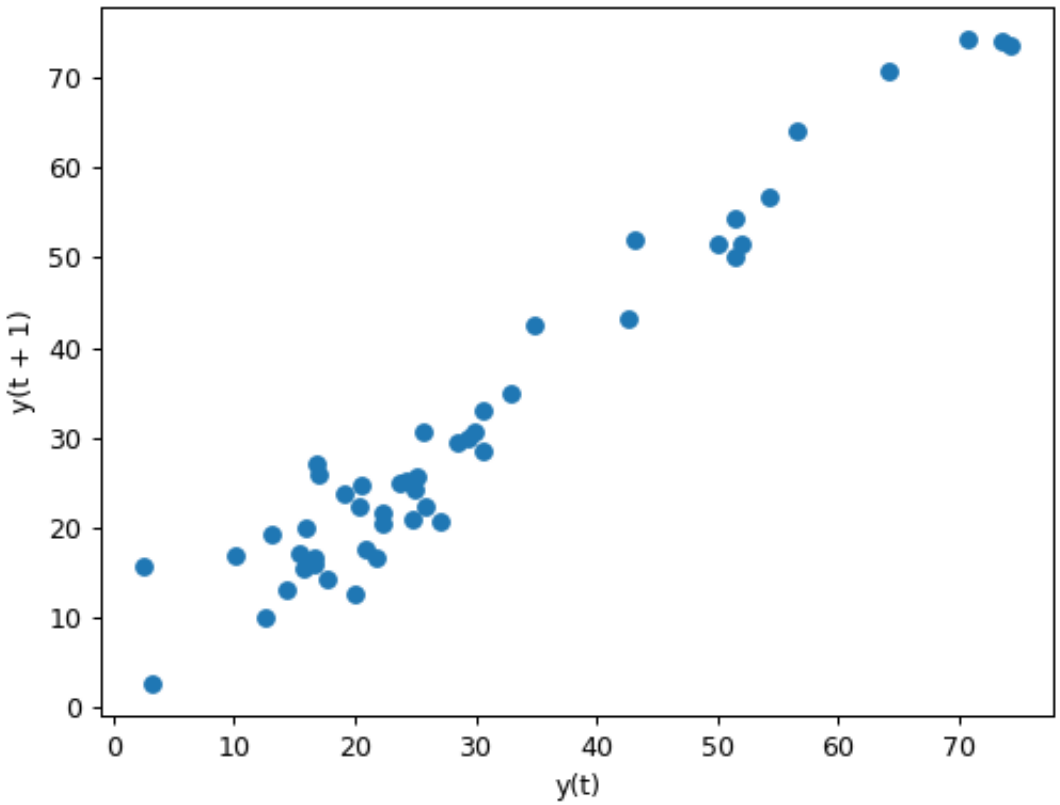
pandas.plotting.**parallel_coordinates**(*frame*, *class_column*, *cols=None*, *ax=None*, *color=None*, *use_columns=False*, *xticks=None*, *colormap=None*, *axvlines=True*, *axvlines_kwds=None*, *sort_labels=False*, ***kwargs*)

Parallel coordinates plotting.

Parameters

frame [DataFrame]


70
60
50
40
30
20
10
0
0
10
20
30
40
50


y(t + 1)
y(t)
0
10
20
30
40
50
60
70

class_column [str] Column name containing class names.

cols [list, optional] A list of column names to use.

ax [matplotlib.axis, optional] Matplotlib axis object.

color [list or tuple, optional] Colors to use for the different classes.

use_columns [bool, optional] If true, columns will be used as xticks.

xticks [list or tuple, optional] A list of values to use for xticks.

colormap [str or matplotlib colormap, default None] Colormap to use for line colors.

axvlines [bool, optional] If true, vertical lines will be added at each xtick.

axvlines_kwds [keywords, optional] Options to be passed to axvline method for vertical lines.

sort_labels [bool, default False] Sort class_column labels, useful when assigning colors.

****kwargs** Options to pass to matplotlib plotting method.

Returns

class:*matplotlib.axis.Axes*

Examples

```
>>> df = pd.read_csv(
...     'https://raw.github.com/pandas-dev/'
...     'pandas/master/pandas/tests/io/data/csv/iris.csv'
... )
>>> pd.plotting.parallel_coordinates(
...     df, 'Name', color=('#556270', '#4ECDC4', '#C7F464')
... )
```

3.13.8 pandas.plotting.plot_params

pandas.plotting.**plot_params = {'xaxis.compat': False}**

Stores pandas plotting options.

Allows for parameter aliasing so you can just use parameter names that are the same as the plot function parameters, but is stored in a canonical format that makes it easy to breakdown into groups later.

3.13.9 pandas.plotting.radviz

pandas.plotting.**radviz**(*frame*, *class_column*, *ax=None*, *color=None*, *colormap=None*, ***kwds*)

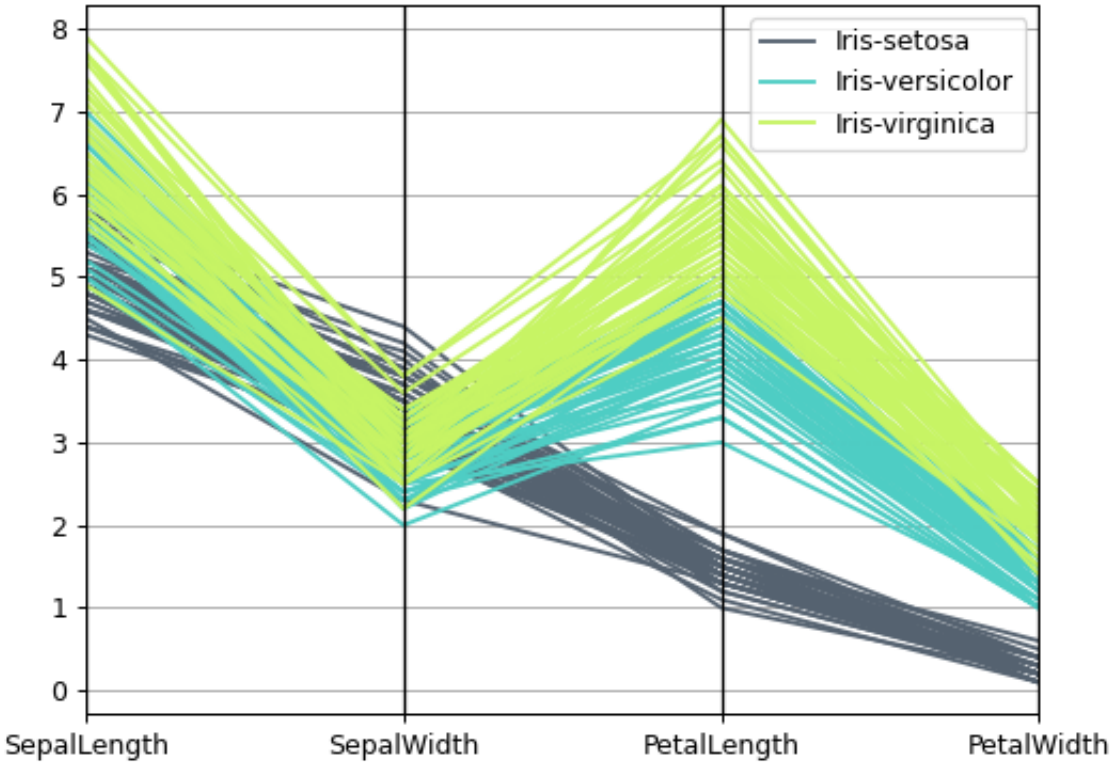
Plot a multidimensional dataset in 2D.

Each Series in the DataFrame is represented as a evenly distributed slice on a circle. Each data point is rendered in the circle according to the value on each Series. Highly correlated *Series* in the *DataFrame* are placed closer on the unit circle.

RadViz allow to project a N-dimensional data set into a 2D space where the influence of each dimension can be interpreted as a balance between the influence of all dimensions.

More info available at the original article describing RadViz.

Parameters


Iris-setosa
Iris-versicolor
Iris-virginica
8
7
6
5
4
3
2
1
0
SepalLength
SepalWidth
PetalLength
PetalWidth

frame [*DataFrame*] Object holding the data.

class_column [str] Column name containing the name of the data point category.

ax [`matplotlib.axes.Axes`, optional] A plot instance to which to add the information.

color [list[str] or tuple[str], optional] Assign a color to each category. Example: ['blue', 'green'].

colormap [str or `matplotlib.colors.Colormap`, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

****kwds** Options to pass to matplotlib scatter plotting method.

Returns

class:*matplotlib.axes.Axes*

See also:

`plotting.andrews_curves` Plot clustering visualization.

Examples

```
>>> df = pd.DataFrame(
...     {
...         'SepalLength': [6.5, 7.7, 5.1, 5.8, 7.6, 5.0, 5.4, 4.6, 6.7, 4.6],
...         'SepalWidth': [3.0, 3.8, 3.8, 2.7, 3.0, 2.3, 3.0, 3.2, 3.3, 3.6],
...         'PetalLength': [5.5, 6.7, 1.9, 5.1, 6.6, 3.3, 4.5, 1.4, 5.7, 1.0],
...         'PetalWidth': [1.8, 2.2, 0.4, 1.9, 2.1, 1.0, 1.5, 0.2, 2.1, 0.2],
...         'Category': [
...             'virginica',
...             'virginica',
...             'setosa',
...             'virginica',
...             'virginica',
...             'versicolor',
...             'versicolor',
...             'setosa',
...             'virginica',
...             'setosa'
...         ]
...     }
... )
>>> pd.plotting.radviz(df, 'Category')
```

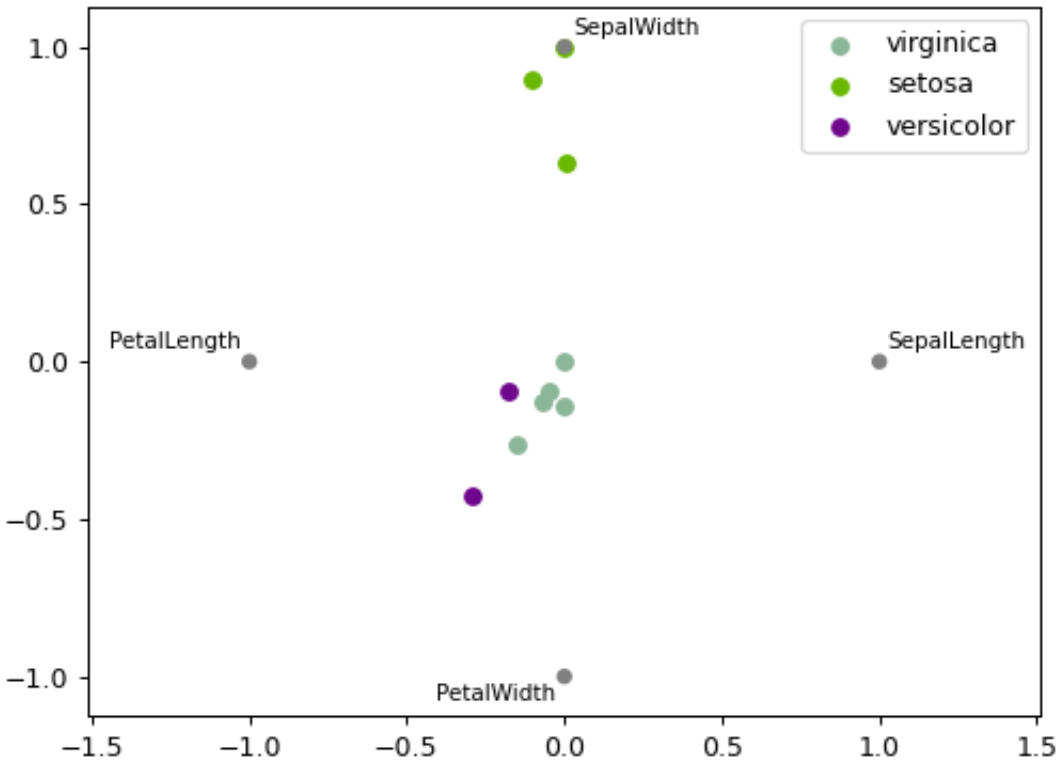
3.13.10 pandas.plotting.register_matplotlib_converters

pandas.plotting.**register_matplotlib_converters**()

Register pandas formatters and converters with matplotlib.

This function modifies the global `matplotlib.units.registry` dictionary. pandas adds custom converters for

- pd.Timestamp
- pd.Period
- np.datetime64
- datetime.datetime
- datetime.date
- datetime.time


SepalWidth
virginica
setosa
versicolor
PetalLength
SepalLength
PetalWidth
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

See also:

deregister_matplotlib_converters Remove pandas formatters and converters.

3.13.11 pandas.plotting.scatter_matrix

pandas.plotting.**scatter_matrix**(*frame*, *alpha=0.5*, *figsize=None*, *ax=None*, *grid=False*, *diagonal='hist'*, *marker='.'*, *density_kwds=None*, *hist_kwds=None*, *range_padding=0.05*, ***kwargs*)

Draw a matrix of scatter plots.

Parameters

frame [DataFrame]

alpha [float, optional] Amount of transparency applied.

figsize [(float,float), optional] A tuple (width, height) in inches.

ax [Matplotlib axis object, optional]

grid [bool, optional] Setting this to True will show the grid.

diagonal [{'hist', 'kde'}] Pick between 'kde' and 'hist' for either Kernel Density Estimation or Histogram plot in the diagonal.

marker [str, optional] Matplotlib marker type, default '.'.

density_kwds [keywords] Keyword arguments to be passed to kernel density estimate plot.

hist_kwds [keywords] Keyword arguments to be passed to hist function.

range_padding [float, default 0.05] Relative extension of axis range in x and y with respect to (x_max - x_min) or (y_max - y_min).

****kwargs** Keyword arguments to be passed to scatter function.

Returns

numpy.ndarray A matrix of scatter plots.

Examples

```
>>> df = pd.DataFrame(np.random.randn(1000, 4), columns=['A','B','C','D'])
>>> pd.plotting.scatter_matrix(df, alpha=0.2)
```

3.13.12 pandas.plotting.table

pandas.plotting.**table**(*ax*, *data*, *rowLabels=None*, *colLabels=None*, ***kwargs*)

Helper function to convert DataFrame and Series to matplotlib.table.

Parameters

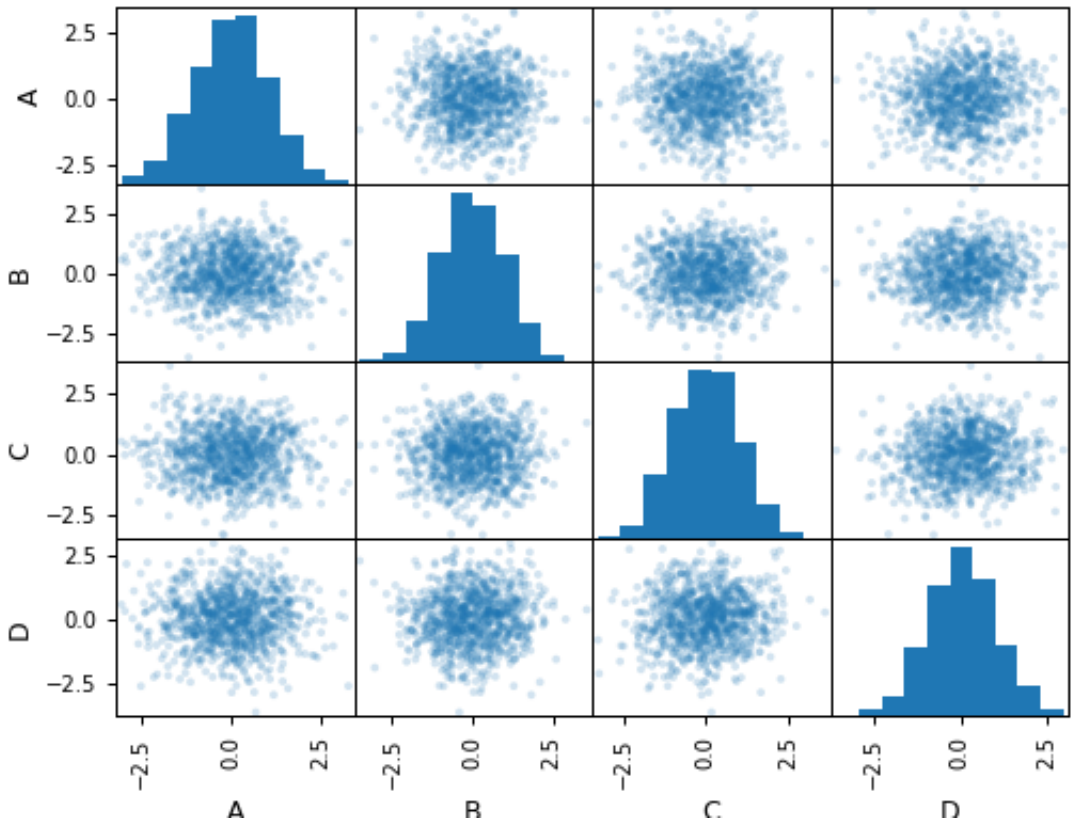
ax [Matplotlib axes object]

data [DataFrame or Series] Data for table contents.

****kwargs** Keyword arguments to be passed to matplotlib.table.table. If *rowLabels* or *colLabels* is not specified, data index or column name will be used.

Returns

matplotlib table object


A
B
C
D
2.5
0.0
−2.5

3.14 General utility functions

3.14.1 Working with options

describe_option(pat[, _print_desc])	Prints the description for one or more registered options.
reset_option(pat)	Reset one or more options to their default value.
get_option(pat)	Retrieves the value of the specified option.
set_option(pat, value)	Sets the value of the specified option.
option_context(*args)	Context manager to temporarily set options in the *with* statement context.

pandas.describe_option

pandas.**describe_option**(*pat*, *_print_desc=False*) **= <pandas._config.config.CallableDynamicDoc object>**

Prints the description for one or more registered options.

Call with not arguments to get a listing for all registered options.

Available options:

- compute.[use_bottleneck, use_numba, use_numexpr]
- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
- display.html.[border, table_schema, use_mathjax]
- display.[large_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
- display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
- display.unicode.[ambiguous_as_wide, east_asian_width]
- display.[width]
- io.excel.ods.[reader, writer]
- io.excel.xls.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xlsm.[reader, writer]
- io.excel.xlsx.[reader, writer]
- io.hdf.[default_format, dropna_table]
- io.parquet.[engine]
- mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
- plotting.[backend]
- plotting.matplotlib.[register_converters]

Parameters

pat [str] Regexp pattern. All matching keys will have their description displayed.

_print_desc [bool, default True] If True (default) the description(s) will be printed to stdout. Otherwise, the description(s) will be returned as a unicode string (for testing).

Returns

None by default, the description(s) as a unicode string if _print_desc

is False

Notes

The available options with its descriptions:

compute.use_bottleneck [bool] Use the bottleneck library to accelerate if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

compute.use_numba [bool] Use the numba engine option for select operations if it is installed, the default is False Valid values: False,True [default: False] [currently: False]

compute.use_numexpr [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

display.html.border [int] A `border=value` attribute is inserted in the `<table>` tag for the DataFrame HTML repr. [default: 1] [currently: 1]

display.html.table_schema [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

display.html.use_mathjax [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.latex.escape [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

display.latex.longtable :bool This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

display.latex.multicolumn [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

display.latex.multicolumn_format [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]

display.latex.multirow [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

display.max_colwidth [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. A 'None' value means unlimited. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] When pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,'deep' [default: True] [currently: True]

display.min_rows [int] The numbers of rows to show in a truncated view (when *max_rows* is exceeded). Ignored when *max_rows* is set to None or 0. When set to None, follows the value of *max_rows*. [default: 10] [currently: 10]

display.multi_sparse [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision in terms of number of places after the decimal, for regular formatting as well as scientific notation. Similar to `precision` in `numpy.set_printoptions()`. [default: 6] [currently: 6]

display.show_dimensions [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

display.unicode.ambiguous_as_wide [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.unicode.east_asian_width [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.ods.reader [string] The default Excel reader engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.ods.writer [string] The default Excel writer engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.xls.reader [string] The default Excel reader engine for 'xls' files. Available options: auto, xlrd. [de-

fault: auto] [currently: auto]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: auto, xlwt. [default: auto] [currently: auto] (Deprecated, use `` instead.)

io.excel.xlsb.reader [string] The default Excel reader engine for 'xlsb' files. Available options: auto, pyxlsb. [default: auto] [currently: auto]

io.excel.xlsm.reader [string] The default Excel reader engine for 'xlsm' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: auto, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.reader [string] The default Excel reader engine for 'xlsx' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: auto, openpyxl, xlsxwriter. [default: auto] [currently: auto]

io.hdf.default_format [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]

io.parquet.engine [string] The default parquet reader/writer engine. Available options: 'auto', 'pyarrow', 'fastparquet', the default is 'auto' [default: auto] [currently: auto]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use *use_inf_as_na* instead. [default: False] [currently: False] (Deprecated, use *mode.use_inf_as_na* instead.)

plotting.backend [str] The plotting backend to use. The default value is "matplotlib", the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

plotting.matplotlib.register_converters [bool or 'auto'.] Whether to register converters with matplotlib's units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

pandas.reset_option

pandas.**reset_option**(*pat*) **= <pandas._config.config.CallableDynamicDoc object>**

Reset one or more options to their default value.

Pass "all" as argument to reset all options.

Available options:

- compute.[use_bottleneck, use_numba, use_numexpr]
- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
- display.html.[border, table_schema, use_mathjax]
- display.[large_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
- display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
- display.unicode.[ambiguous_as_wide, east_asian_width]

- display.[width]
- io.excel.ods.[reader, writer]
- io.excel.xls.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xlsm.[reader, writer]
- io.excel.xlsx.[reader, writer]
- io.hdf.[default_format, dropna_table]
- io.parquet.[engine]
- mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
- plotting.[backend]
- plotting.matplotlib.[register_converters]

Parameters

pat [str/regex] If specified only options matching *prefix** will be reset. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

Returns

None

Notes

The available options with its descriptions:

compute.use_bottleneck [bool] Use the bottleneck library to accelerate if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

compute.use_numba [bool] Use the numba engine option for select operations if it is installed, the default is False Valid values: False,True [default: False] [currently: False]

compute.use_numexpr [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

display.html.border [int] A `border=value` attribute is inserted in the `<table>` tag for the DataFrame HTML repr. [default: 1] [currently: 1]

display.html.table_schema [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

display.html.use_mathjax [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.latex.escape [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

display.latex.longtable :bool This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

display.latex.multicolumn [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

display.latex.multicolumn_format [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]

display.latex.multirow [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

display.max_colwidth [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. A 'None' value means unlimited. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] When pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,'deep' [default: True] [currently: True]

display.min_rows [int] The numbers of rows to show in a truncated view (when *max_rows* is exceeded). Ignored when *max_rows* is set to None or 0. When set to None, follows the value of *max_rows*. [default: 10] [currently: 10]

display.multi_sparse [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision in terms of number of places after the decimal, for regular formatting as well as scientific notation. Similar to `precision` in `numpy.set_printoptions()`. [default: 6] [currently: 6]

display.show_dimensions [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

display.unicode.ambiguous_as_wide [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.unicode.east_asian_width [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.ods.reader [string] The default Excel reader engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.ods.writer [string] The default Excel writer engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.xls.reader [string] The default Excel reader engine for 'xls' files. Available options: auto, xlrd. [default: auto] [currently: auto]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: auto, xlwt. [default: auto] [currently: auto] (Deprecated, use `` instead.)

io.excel.xlsb.reader [string] The default Excel reader engine for 'xlsb' files. Available options: auto, pyxlsb. [default: auto] [currently: auto]

io.excel.xlsm.reader [string] The default Excel reader engine for 'xlsm' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: auto, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.reader [string] The default Excel reader engine for 'xlsx' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: auto, openpyxl, xlsxwriter. [default: auto] [currently: auto]

io.hdf.default_format [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]

io.parquet.engine [string] The default parquet reader/writer engine. Available options: 'auto', 'pyarrow', 'fastparquet', the default is 'auto' [default: auto] [currently: auto]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use *use_inf_as_na* instead. [default: False] [currently: False] (Deprecated, use *mode.use_inf_as_na* instead.)

plotting.backend [str] The plotting backend to use. The default value is "matplotlib", the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

plotting.matplotlib.register_converters [bool or 'auto'.] Whether to register converters with matplotlib's units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

pandas.get_option

pandas.**get_option**(*pat*) **= <pandas._config.config.CallableDynamicDoc object>**

Retrieves the value of the specified option.

Available options:

- compute.[use_bottleneck, use_numba, use_numexpr]
- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
- display.html.[border, table_schema, use_mathjax]
- display.[large_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
- display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
- display.unicode.[ambiguous_as_wide, east_asian_width]
- display.[width]
- io.excel.ods.[reader, writer]
- io.excel.xls.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xlsm.[reader, writer]
- io.excel.xlsx.[reader, writer]
- io.hdf.[default_format, dropna_table]
- io.parquet.[engine]
- mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
- plotting.[backend]
- plotting.matplotlib.[register_converters]

Parameters

pat [str] Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

Returns

result [the value of the option]

Raises

OptionError [if no such option exists]

Notes

The available options with its descriptions:

compute.use_bottleneck [bool] Use the bottleneck library to accelerate if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

compute.use_numba [bool] Use the numba engine option for select operations if it is installed, the default is False Valid values: False,True [default: False] [currently: False]

compute.use_numexpr [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

display.html.border [int] A `border=value` attribute is inserted in the `<table>` tag for the DataFrame HTML repr. [default: 1] [currently: 1]

display.html.table_schema [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

display.html.use_mathjax [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.latex.escape [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

display.latex.longtable :bool This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

display.latex.multicolumn [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

display.latex.multicolumn_format [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]

display.latex.multirow [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

display.max_colwidth [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. A 'None' value means unlimited. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] When pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,'deep' [default: True] [currently: True]

display.min_rows [int] The numbers of rows to show in a truncated view (when *max_rows* is exceeded). Ignored when *max_rows* is set to None or 0. When set to None, follows the value of *max_rows*. [default: 10] [currently: 10]

display.multi_sparse [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision in terms of number of places after the decimal, for regular formatting as well as scientific notation. Similar to `precision` in `numpy.set_printoptions()`. [default: 6] [currently: 6]

display.show_dimensions [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

display.unicode.ambiguous_as_wide [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.unicode.east_asian_width [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.ods.reader [string] The default Excel reader engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.ods.writer [string] The default Excel writer engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.xls.reader [string] The default Excel reader engine for 'xls' files. Available options: auto, xlrd. [default: auto] [currently: auto]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: auto, xlwt. [default: auto] [currently: auto] (Deprecated, use `` instead.)

io.excel.xlsb.reader [string] The default Excel reader engine for 'xlsb' files. Available options: auto, pyxlsb. [default: auto] [currently: auto]

io.excel.xlsm.reader [string] The default Excel reader engine for 'xlsm' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: auto, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.reader [string] The default Excel reader engine for 'xlsx' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: auto, openpyxl, xlsxwriter. [default: auto] [currently: auto]

io.hdf.default_format [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]

io.parquet.engine [string] The default parquet reader/writer engine. Available options: 'auto', 'pyarrow', 'fastparquet', the default is 'auto' [default: auto] [currently: auto]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use *use_inf_as_na* instead. [default: False] [currently: False] (Deprecated, use *mode.use_inf_as_na* instead.)

plotting.backend [str] The plotting backend to use. The default value is "matplotlib", the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

plotting.matplotlib.register_converters [bool or 'auto'.] Whether to register converters with matplotlib's units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

pandas.set_option

pandas.**set_option**(*pat*, *value*) **= <pandas._config.config.CallableDynamicDoc object>**

Sets the value of the specified option.

Available options:

- compute.[use_bottleneck, use_numba, use_numexpr]
- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
- display.html.[border, table_schema, use_mathjax]
- display.[large_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
- display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
- display.unicode.[ambiguous_as_wide, east_asian_width]
- display.[width]
- io.excel.ods.[reader, writer]
- io.excel.xls.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xlsm.[reader, writer]
- io.excel.xlsx.[reader, writer]
- io.hdf.[default_format, dropna_table]
- io.parquet.[engine]
- mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
- plotting.[backend]
- plotting.matplotlib.[register_converters]

Parameters

pat [str] Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

value [object] New value of option.

Returns

None

Raises

OptionError if no such option exists

Notes

The available options with its descriptions:

compute.use_bottleneck [bool] Use the bottleneck library to accelerate if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

compute.use_numba [bool] Use the numba engine option for select operations if it is installed, the default is False Valid values: False,True [default: False] [currently: False]

compute.use_numexpr [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

display.html.border [int] A `border=value` attribute is inserted in the `<table>` tag for the DataFrame HTML repr. [default: 1] [currently: 1]

display.html.table_schema [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

display.html.use_mathjax [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.latex.escape [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

display.latex.longtable :bool This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

display.latex.multicolumn [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

display.latex.multicolumn_format [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]

display.latex.multirow [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

display.max_colwidth [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. A 'None' value means unlimited. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] When pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,'deep' [default: True] [currently: True]

display.min_rows [int] The numbers of rows to show in a truncated view (when *max_rows* is exceeded). Ignored when *max_rows* is set to None or 0. When set to None, follows the value of *max_rows*. [default: 10] [currently: 10]

display.multi_sparse [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision in terms of number of places after the decimal, for regular formatting as well as scientific notation. Similar to `precision` in `numpy.set_printoptions()`. [default: 6] [currently: 6]

display.show_dimensions [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

display.unicode.ambiguous_as_wide [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.unicode.east_asian_width [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.ods.reader [string] The default Excel reader engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.ods.writer [string] The default Excel writer engine for 'ods' files. Available options: auto, odf. [default: auto] [currently: auto]

io.excel.xls.reader [string] The default Excel reader engine for 'xls' files. Available options: auto, xlrd. [default: auto] [currently: auto]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: auto, xlwt. [default: auto] [currently: auto] (Deprecated, use `` instead.)

io.excel.xlsb.reader [string] The default Excel reader engine for 'xlsb' files. Available options: auto, pyxlsb. [default: auto] [currently: auto]

io.excel.xlsm.reader [string] The default Excel reader engine for 'xlsm' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: auto, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.reader [string] The default Excel reader engine for 'xlsx' files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: auto, openpyxl, xlsxwriter. [default: auto] [currently: auto]

io.hdf.default_format [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]

io.parquet.engine [string] The default parquet reader/writer engine. Available options: 'auto', 'pyarrow', 'fastparquet', the default is 'auto' [default: auto] [currently: auto]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use *use_inf_as_na* instead. [default: False] [currently: False] (Deprecated, use *mode.use_inf_as_na* instead.)

plotting.backend [str] The plotting backend to use. The default value is "matplotlib", the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

plotting.matplotlib.register_converters [bool or 'auto'.] Whether to register converters with matplotlib's units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

pandas.option_context

class pandas.**option_context**(**args*)

Context manager to temporarily set options in the *with* statement context.

You need to invoke as `option_context(pat, val, [(pat, val), ...])`.

Examples

```
>>> with option_context('display.max_rows', 10, 'display.max_columns', 5):
...     ...
```

Methods

__call__(func)	Call self as a function.

pandas.option_context.__call__

option_context.**__call__**(*func*)

Call self as a function.

3.14.2 Testing functions

testing.assert_frame_equal(left, right[, ...])	Check that left and right DataFrame are equal.
testing.assert_series_equal(left, right[, ...])	Check that left and right Series are equal.
testing.assert_index_equal(left, right[, ...])	Check that left and right Index are equal.
testing.assert_extension_array_equal(left, right)	Check that left and right ExtensionArrays are equal.

pandas.testing.assert_frame_equal

pandas.testing.**assert_frame_equal**(*left*, *right*, *check_dtype=True*, *check_index_type='equiv'*, *check_column_type='equiv'*, *check_frame_type=True*, *check_less_precise=<object object>*, *check_names=True*, *by_blocks=False*, *check_exact=False*, *check_datetimelike_compat=False*, *check_categorical=True*, *check_like=False*, *check_freq=True*, *check_flags=True*, *rtol=1e-05*, *atol=1e-08*, *obj='DataFrame'*)

Check that left and right DataFrame are equal.

This function is intended to compare two DataFrames and output any differences. Is is mostly intended for use in unit tests. Additional parameters allow varying the strictness of the equality checks performed.

Parameters

left [DataFrame] First DataFrame to compare.

right [DataFrame] Second DataFrame to compare.

check_dtype [bool, default True] Whether to check the DataFrame dtype is identical.

check_index_type [bool or {'equiv'}, default 'equiv'] Whether to check the Index class, dtype and inferred_type are identical.

check_column_type [bool or {'equiv'}, default 'equiv'] Whether to check the columns class, dtype and inferred_type are identical. Is passed as the `exact` argument of *`assert_index_equal()`*.

check_frame_type [bool, default True] Whether to check the DataFrame class is identical.

check_less_precise [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

When comparing two numbers, if the first number has magnitude less than 1e-5, we compare the two numbers directly and check whether they are equivalent within the specified precision. Otherwise, we compare the **ratio** of the second number to the first number and check whether it is equivalent to 1 within the specified precision.

Deprecated since version 1.1.0: Use *rtol* and *atol* instead to define relative/absolute tolerance, respectively. Similar to `math.isclose()`.

check_names [bool, default True] Whether to check that the *names* attribute for both the *index* and *column* attributes of the DataFrame is identical.

by_blocks [bool, default False] Specify how to compare internal data. If False, compare by columns. If True, compare by blocks.

check_exact [bool, default False] Whether to compare number exactly.

check_datetimelike_compat [bool, default False] Compare datetime-like which is comparable ignoring dtype.

check_categorical [bool, default True] Whether to compare internal Categorical exactly.

check_like [bool, default False] If True, ignore the order of index & columns. Note: index labels must match their respective rows (same as in columns) - same labels must be with the same data.

check_freq [bool, default True] Whether to check the *freq* attribute on a DatetimeIndex or TimedeltaIndex.

New in version 1.1.0.

check_flags [bool, default True] Whether to check the *flags* attribute.

rtol [float, default 1e-5] Relative tolerance. Only used when check_exact is False.

New in version 1.1.0.

atol [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.

New in version 1.1.0.

obj [str, default 'DataFrame'] Specify object name being compared, internally used to show appropriate assertion message.

See also:

`assert_series_equal` Equivalent method for asserting Series equality.
`DataFrame.equals` Check DataFrame equality.

Examples

This example shows comparing two DataFrames that are equal but with columns of differing dtypes.

```
>>> from pandas._testing import assert_frame_equal
>>> df1 = pd.DataFrame({'a': [1, 2], 'b': [3, 4]})
>>> df2 = pd.DataFrame({'a': [1, 2], 'b': [3.0, 4.0]})
```

df1 equals itself.

```
>>> assert_frame_equal(df1, df1)
```

df1 differs from df2 as column 'b' is of a different type.

```
>>> assert_frame_equal(df1, df2)
Traceback (most recent call last):
...
AssertionError: Attributes of DataFrame.iloc[:, 1] (column name="b") are different
```

Attribute "dtype" are different [left]: int64 [right]: float64

Ignore differing dtypes in columns with check_dtype.

```
>>> assert_frame_equal(df1, df2, check_dtype=False)
```

pandas.testing.assert_series_equal

pandas.testing.**assert_series_equal**(*left*, *right*, *check_dtype=True*, *check_index_type='equiv'*, *check_series_type=True*, *check_less_precise=<object object>*, *check_names=True*, *check_exact=False*, *check_datetimelike_compat=False*, *check_categorical=True*, *check_category_order=True*, *check_freq=True*, *check_flags=True*, *rtol=1e-05*, *atol=1e-08*, *obj='Series'*)

Check that left and right Series are equal.

Parameters

left [Series]

right [Series]

check_dtype [bool, default True] Whether to check the Series dtype is identical.

check_index_type [bool or {'equiv'}, default 'equiv'] Whether to check the Index class, dtype and inferred_type are identical.

check_series_type [bool, default True] Whether to check the Series class is identical.

check_less_precise [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

When comparing two numbers, if the first number has magnitude less than 1e-5, we compare the two numbers directly and check whether they are equivalent within the specified precision. Otherwise, we compare the **ratio** of the second number to the first number and check whether it is equivalent to 1 within the specified precision.

Deprecated since version 1.1.0: Use *rtol* and *atol* instead to define relative/absolute tolerance, respectively. Similar to `math.isclose()`.

check_names [bool, default True] Whether to check the Series and Index names attribute.

check_exact [bool, default False] Whether to compare number exactly.

check_datetimelike_compat [bool, default False] Compare datetime-like which is comparable ignoring dtype.

check_categorical [bool, default True] Whether to compare internal Categorical exactly.

check_category_order [bool, default True] Whether to compare category order of internal Categoricals.

New in version 1.0.2.

check_freq [bool, default True] Whether to check the *freq* attribute on a DatetimeIndex or TimedeltaIndex.

New in version 1.1.0.

check_flags [bool, default True] Whether to check the *flags* attribute.

New in version 1.2.0.

rtol [float, default 1e-5] Relative tolerance. Only used when check_exact is False.

New in version 1.1.0.

atol [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.

New in version 1.1.0.

obj [str, default 'Series'] Specify object name being compared, internally used to show appropriate assertion message.

Examples

```
>>> from pandas.testing import assert_series_equal
>>> a = pd.Series([1, 2, 3, 4])
>>> b = pd.Series([1, 2, 3, 4])
>>> assert_series_equal(a, b)
```

pandas.testing.assert_index_equal

pandas.testing.**assert_index_equal**(*left*, *right*, *exact='equiv'*, *check_names=True*, *check_less_precise=<object object>*, *check_exact=True*, *check_categorical=True*, *check_order=True*, *rtol=1e-05*, *atol=1e-08*, *obj='Index'*)

Check that left and right Index are equal.

Parameters

left [Index]

right [Index]

exact [bool or {'equiv'}, default 'equiv'] Whether to check the Index class, dtype and inferred_type are identical. If 'equiv', then RangeIndex can be substituted for Int64Index as well.

check_names [bool, default True] Whether to check the names attribute.

check_less_precise [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

Deprecated since version 1.1.0: Use *rtol* and *atol* instead to define relative/absolute tolerance, respectively. Similar to `math.isclose()`.

check_exact [bool, default True] Whether to compare number exactly.

check_categorical [bool, default True] Whether to compare internal Categorical exactly.

check_order [bool, default True] Whether to compare the order of index entries as well as their values. If True, both indexes must contain the same elements, in the same order. If False, both indexes must contain the same elements, but in any order.

New in version 1.2.0.

rtol [float, default 1e-5] Relative tolerance. Only used when check_exact is False.

New in version 1.1.0.

atol [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.

New in version 1.1.0.

obj [str, default 'Index'] Specify object name being compared, internally used to show appropriate assertion message.

Examples

```
>>> from pandas.testing import assert_index_equal
>>> a = pd.Index([1, 2, 3])
>>> b = pd.Index([1, 2, 3])
>>> assert_index_equal(a, b)
```

pandas.testing.assert_extension_array_equal

pandas.testing.**assert_extension_array_equal**(*left*, *right*, *check_dtype=True*, *index_values=None*, *check_less_precise=<object object>*, *check_exact=False*, *rtol=1e-05*, *atol=1e-08*)

Check that left and right ExtensionArrays are equal.

Parameters

left, right [ExtensionArray] The two arrays to compare.

check_dtype [bool, default True] Whether to check if the ExtensionArray dtypes are identical.

index_values [numpy.ndarray, default None] Optional index (shared by both left and right), used in output.

check_less_precise [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

Deprecated since version 1.1.0: Use *rtol* and *atol* instead to define relative/absolute tolerance, respectively. Similar to `math.isclose()`.

check_exact [bool, default False] Whether to compare number exactly.

rtol [float, default 1e-5] Relative tolerance. Only used when check_exact is False.

New in version 1.1.0.

atol [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.

New in version 1.1.0.

Notes

Missing values are checked separately from valid values. A mask of missing values is computed for each and checked to match. The remaining all-valid values are cast to object dtype and checked.

Examples

```
>>> from pandas.testing import assert_extension_array_equal
>>> a = pd.Series([1, 2, 3, 4])
>>> b, c = a.array, a.array
>>> assert_extension_array_equal(b, c)
```

3.14.3 Exceptions and warnings

errors.AccessorRegistrationWarning	Warning for attribute conflicts in accessor registration.
errors.DtypeWarning	Warning raised when reading different dtypes in a column from a file.
errors.DuplicateLabelError	Error raised when an operation would introduce duplicate labels.
errors.EmptyDataError	Exception that is thrown in *pd.read_csv* (by both the C and Python engines) when empty data or header is encountered.
errors.InvalidIndexError	Exception raised when attempting to use an invalid index key.
errors.MergeError	Error raised when problems arise during merging due to problems with input data.
errors.NullFrequencyError	Error raised when a null *freq* attribute is used in an operation that needs a non-null frequency, particularly *DatetimeIndex.shift*, *TimedeltaIndex.shift*, *PeriodIndex.shift*.
errors.NumbaUtilError	Error raised for unsupported Numba engine routines.
errors.OutOfBoundsDatetime	
errors.OutOfBoundsTimedelta	Raised when encountering a timedelta value that cannot be represented as a timedelta64[ns].
errors.ParserError	Exception that is raised by an error encountered in parsing file contents.
errors.ParserWarning	Warning raised when reading a file that doesn't use the default 'c' parser.
errors.PerformanceWarning	Warning raised when there is a possible performance impact.
errors.UnsortedIndexError	Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted.

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errors.UnsupportedFunctionCall	Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g.

pandas.errors.AccessorRegistrationWarning

exception pandas.errors.**AccessorRegistrationWarning**
Warning for attribute conflicts in accessor registration.

pandas.errors.DtypeWarning

exception pandas.errors.**DtypeWarning**
Warning raised when reading different dtypes in a column from a file.

Raised for a dtype incompatibility. This can happen whenever *read_csv* or *read_table* encounter non-uniform dtypes in a column(s) of a given CSV file.

See also:

read_csv Read CSV (comma-separated) file into a DataFrame.
read_table Read general delimited file into a DataFrame.

Notes

This warning is issued when dealing with larger files because the dtype checking happens per chunk read.

Despite the warning, the CSV file is read with mixed types in a single column which will be an object type. See the examples below to better understand this issue.

Examples

This example creates and reads a large CSV file with a column that contains *int* and *str*.

```
>>> df = pd.DataFrame({'a': (['1'] * 100000 + ['X'] * 100000 +
...                          ['1'] * 100000),
...                    'b': ['b'] * 300000})
>>> df.to_csv('test.csv', index=False)
>>> df2 = pd.read_csv('test.csv')
... # DtypeWarning: Columns (0) have mixed types
```

Important to notice that `df2` will contain both *str* and *int* for the same input, '1'.

```
>>> df2.iloc[262140, 0]
'1'
>>> type(df2.iloc[262140, 0])
<class 'str'>
>>> df2.iloc[262150, 0]
1
>>> type(df2.iloc[262150, 0])
<class 'int'>
```

One way to solve this issue is using the *dtype* parameter in the *read_csv* and *read_table* functions to explicit the conversion:

```
>>> df2 = pd.read_csv('test.csv', sep=',', dtype={'a': str})
```

No warning was issued.

```
>>> import os
>>> os.remove('test.csv')
```

pandas.errors.DuplicateLabelError

exception pandas.errors.**DuplicateLabelError**

Error raised when an operation would introduce duplicate labels.

New in version 1.2.0.

Examples

```
>>> s = pd.Series([0, 1, 2], index=['a', 'b', 'c']).set_flags(
...     allows_duplicate_labels=False
... )
>>> s.reindex(['a', 'a', 'b'])
Traceback (most recent call last):
   ...
DuplicateLabelError: Index has duplicates.
      positions
label
a        [0, 1]
```

pandas.errors.EmptyDataError

exception pandas.errors.**EmptyDataError**

Exception that is thrown in *pd.read_csv* (by both the C and Python engines) when empty data or header is encountered.

pandas.errors.InvalidIndexError

exception pandas.errors.**InvalidIndexError**

Exception raised when attempting to use an invalid index key.

New in version 1.1.0.

pandas.errors.MergeError

exception pandas.errors.**MergeError**

Error raised when problems arise during merging due to problems with input data. Subclass of *ValueError*.

pandas.errors.NullFrequencyError

exception pandas.errors.**NullFrequencyError**
Error raised when a null *freq* attribute is used in an operation that needs a non-null frequency, particularly *DatetimeIndex.shift*, *TimedeltaIndex.shift*, *PeriodIndex.shift*.

pandas.errors.NumbaUtilError

exception pandas.errors.**NumbaUtilError**
Error raised for unsupported Numba engine routines.

pandas.errors.OutOfBoundsDatetime

exception pandas.errors.**OutOfBoundsDatetime**

pandas.errors.OutOfBoundsTimedelta

exception pandas.errors.**OutOfBoundsTimedelta**
Raised when encountering a timedelta value that cannot be represented as a timedelta64[ns].

pandas.errors.ParserError

exception pandas.errors.**ParserError**
Exception that is raised by an error encountered in parsing file contents.

This is a generic error raised for errors encountered when functions like *read_csv* or *read_html* are parsing contents of a file.

See also:

read_csv Read CSV (comma-separated) file into a DataFrame.
read_html Read HTML table into a DataFrame.

pandas.errors.ParserWarning

exception pandas.errors.**ParserWarning**
Warning raised when reading a file that doesn't use the default 'c' parser.

Raised by *pd.read_csv* and *pd.read_table* when it is necessary to change parsers, generally from the default 'c' parser to 'python'.

It happens due to a lack of support or functionality for parsing a particular attribute of a CSV file with the requested engine.

Currently, 'c' unsupported options include the following parameters:
1. *sep* other than a single character (e.g. regex separators)
2. *skipfooter* higher than 0
3. *sep=None* with *delim_whitespace=False*

The warning can be avoided by adding *engine='python'* as a parameter in *pd.read_csv* and *pd.read_table* methods.

See also:

pd.read_csv Read CSV (comma-separated) file into DataFrame.

pd.read_table Read general delimited file into DataFrame.

Examples

Using a *sep* in *pd.read_csv* other than a single character:

```
>>> import io
>>> csv = '''a;b;c
...           1;1,8
...           1;2,1'''
>>> df = pd.read_csv(io.StringIO(csv), sep='[;,]')
... # ParserWarning: Falling back to the 'python' engine...
```

Adding *engine='python'* to *pd.read_csv* removes the Warning:

```
>>> df = pd.read_csv(io.StringIO(csv), sep='[;,]', engine='python')
```

pandas.errors.PerformanceWarning

exception pandas.errors.**PerformanceWarning**
Warning raised when there is a possible performance impact.

pandas.errors.UnsortedIndexError

exception pandas.errors.**UnsortedIndexError**
Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted. Subclass of *KeyError*.

pandas.errors.UnsupportedFunctionCall

exception pandas.errors.**UnsupportedFunctionCall**
Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g. `np.cumsum(groupby_object)`.

3.14.4 Data types related functionality

api.types.union_categoricals(to_union[, ...])	Combine list-like of Categorical-like, unioning categories.
api.types.infer_dtype	Efficiently infer the type of a passed val, or list-like array of values.
api.types.pandas_dtype(dtype)	Convert input into a pandas only dtype object or a numpy dtype object.

pandas.api.types.union_categoricals

pandas.api.types.**union_categoricals**(*to_union*, *sort_categories=False*, *ignore_order=False*)

Combine list-like of Categorical-like, unioning categories.

All categories must have the same dtype.

Parameters

to_union [list-like] Categorical, CategoricalIndex, or Series with dtype='category'.

sort_categories [bool, default False] If true, resulting categories will be lexsorted, otherwise they will be ordered as they appear in the data.

ignore_order [bool, default False] If true, the ordered attribute of the Categoricals will be ignored. Results in an unordered categorical.

Returns

Categorical

Raises

TypeError

- all inputs do not have the same dtype
- all inputs do not have the same ordered property
- all inputs are ordered and their categories are not identical
- sort_categories=True and Categoricals are ordered

ValueError Empty list of categoricals passed

Notes

To learn more about categories, see link

Examples

```
>>> from pandas.api.types import union_categoricals
```

If you want to combine categoricals that do not necessarily have the same categories, *union_categoricals* will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```
>>> a = pd.Categorical(["b", "c"])
>>> b = pd.Categorical(["a", "b"])
>>> union_categoricals([a, b])
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']
```

By default, the resulting categories will be ordered as they appear in the *categories* of the data. If you want the categories to be lexsorted, use *sort_categories=True* argument.

```
>>> union_categoricals([a, b], sort_categories=True)
['b', 'c', 'a', 'b']
Categories (3, object): ['a', 'b', 'c']
```

union_categoricals also works with the case of combining two categoricals of the same categories and order information (e.g. what you could also *append* for).

```
>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "a"], ordered=True)
>>> union_categoricals([a, b])
['a', 'b', 'a', 'b', 'a']
Categories (2, object): ['a' < 'b']
```

Raises *TypeError* because the categories are ordered and not identical.

```
>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "c"], ordered=True)
>>> union_categoricals([a, b])
Traceback (most recent call last):
    ...
TypeError: to union ordered Categoricals, all categories must be the same
```

New in version 0.20.0

Ordered categoricals with different categories or orderings can be combined by using the *ignore_ordered=True* argument.

```
>>> a = pd.Categorical(["a", "b", "c"], ordered=True)
>>> b = pd.Categorical(["c", "b", "a"], ordered=True)
>>> union_categoricals([a, b], ignore_order=True)
['a', 'b', 'c', 'c', 'b', 'a']
Categories (3, object): ['a', 'b', 'c']
```

union_categoricals also works with a *CategoricalIndex*, or *Series* containing categorical data, but note that the resulting array will always be a plain *Categorical*

```
>>> a = pd.Series(["b", "c"], dtype='category')
>>> b = pd.Series(["a", "b"], dtype='category')
>>> union_categoricals([a, b])
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']
```

pandas.api.types.infer_dtype

pandas.api.types.**infer_dtype**()

Efficiently infer the type of a passed val, or list-like array of values. Return a string describing the type.

Parameters

value [scalar, list, ndarray, or pandas type]

skipna [bool, default True] Ignore NaN values when inferring the type.

Returns

str Describing the common type of the input data.

Results can include:

- **string**
- **bytes**
- **floating**
- **integer**
- **mixed-integer**

- **mixed-integer-float**
- **decimal**
- **complex**
- **categorical**
- **boolean**
- **datetime64**
- **datetime**
- **date**
- **timedelta64**
- **timedelta**
- **time**
- **period**
- **mixed**

Raises

TypeError If ndarray-like but cannot infer the dtype

Notes

- 'mixed' is the catchall for anything that is not otherwise specialized
- 'mixed-integer-float' are floats and integers
- 'mixed-integer' are integers mixed with non-integers

Examples

```
>>> infer_dtype(['foo', 'bar'])
'string'
```

```
>>> infer_dtype(['a', np.nan, 'b'], skipna=True)
'string'
```

```
>>> infer_dtype(['a', np.nan, 'b'], skipna=False)
'mixed'
```

```
>>> infer_dtype([b'foo', b'bar'])
'bytes'
```

```
>>> infer_dtype([1, 2, 3])
'integer'
```

```
>>> infer_dtype([1, 2, 3.5])
'mixed-integer-float'
```

```
>>> infer_dtype([1.0, 2.0, 3.5])
'floating'
```

```
>>> infer_dtype(['a', 1])
'mixed-integer'
```

```
>>> infer_dtype([Decimal(1), Decimal(2.0)])
'decimal'
```

```
>>> infer_dtype([True, False])
'boolean'
```

```
>>> infer_dtype([True, False, np.nan])
'mixed'
```

```
>>> infer_dtype([pd.Timestamp('20130101')])
'datetime'
```

```
>>> infer_dtype([datetime.date(2013, 1, 1)])
'date'
```

```
>>> infer_dtype([np.datetime64('2013-01-01')])
'datetime64'
```

```
>>> infer_dtype([datetime.timedelta(0, 1, 1)])
'timedelta'
```

```
>>> infer_dtype(pd.Series(list('aabc')).astype('category'))
'categorical'
```

pandas.api.types.pandas_dtype

pandas.api.types.**pandas_dtype**(*dtype*)

Convert input into a pandas only dtype object or a numpy dtype object.

Parameters

dtype [object to be converted]

Returns

np.dtype or a pandas dtype

Raises

TypeError if not a dtype

Dtype introspection

api.types.is_bool_dtype(arr_or_dtype)	Check whether the provided array or dtype is of a boolean dtype.
api.types.is_categorical_dtype(arr_or_dtype)	Check whether an array-like or dtype is of the Categorical dtype.
api.types.is_complex_dtype(arr_or_dtype)	Check whether the provided array or dtype is of a complex dtype.

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api.types.is_datetime64_any_dtype(arr_or_dtype)	Check whether the provided array or dtype is of the datetime64 dtype.
api.types.is_datetime64_dtype(arr_or_dtype)	Check whether an array-like or dtype is of the datetime64 dtype.
api.types.is_datetime64_ns_dtype(arr_or_dtype)	Check whether the provided array or dtype is of the datetime64[ns] dtype.
api.types.is_datetime64tz_dtype(arr_or_dtype)	Check whether an array-like or dtype is of a DatetimeTZDtype dtype.
api.types.is_extension_type(arr)	(DEPRECATED) Check whether an array-like is of a pandas extension class instance.
api.types.is_extension_array_dtype(arr_or_dtype)	Check if an object is a pandas extension array type.
api.types.is_float_dtype(arr_or_dtype)	Check whether the provided array or dtype is of a float dtype.
api.types.is_int64_dtype(arr_or_dtype)	Check whether the provided array or dtype is of the int64 dtype.
api.types.is_integer_dtype(arr_or_dtype)	Check whether the provided array or dtype is of an integer dtype.
api.types.is_interval_dtype(arr_or_dtype)	Check whether an array-like or dtype is of the Interval dtype.
api.types.is_numeric_dtype(arr_or_dtype)	Check whether the provided array or dtype is of a numeric dtype.
api.types.is_object_dtype(arr_or_dtype)	Check whether an array-like or dtype is of the object dtype.
api.types.is_period_dtype(arr_or_dtype)	Check whether an array-like or dtype is of the Period dtype.
api.types.is_signed_integer_dtype(arr_or_dtype)	Check whether the provided array or dtype is of a signed integer dtype.
api.types.is_string_dtype(arr_or_dtype)	Check whether the provided array or dtype is of the string dtype.
api.types.is_timedelta64_dtype(arr_or_dtype)	Check whether an array-like or dtype is of the timedelta64 dtype.
api.types.is_timedelta64_ns_dtype(arr_or_dtype)	Check whether the provided array or dtype is of the timedelta64[ns] dtype.
api.types.is_unsigned_integer_dtype(arr_or_dtype)	Check whether the provided array or dtype is of an unsigned integer dtype.
api.types.is_sparse(arr)	Check whether an array-like is a 1-D pandas sparse array.

pandas.api.types.is_bool_dtype

pandas.api.types.**is_bool_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of a boolean dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of a boolean dtype.

Notes

An ExtensionArray is considered boolean when the `_is_boolean` attribute is set to True.

Examples

```
>>> is_bool_dtype(str)
False
>>> is_bool_dtype(int)
False
>>> is_bool_dtype(bool)
True
>>> is_bool_dtype(np.bool_)
True
>>> is_bool_dtype(np.array(['a', 'b']))
False
>>> is_bool_dtype(pd.Series([1, 2]))
False
>>> is_bool_dtype(np.array([True, False]))
True
>>> is_bool_dtype(pd.Categorical([True, False]))
True
>>> is_bool_dtype(pd.arrays.SparseArray([True, False]))
True
```

pandas.api.types.is_categorical_dtype

pandas.api.types.**is_categorical_dtype**(*arr_or_dtype*)

Check whether an array-like or dtype is of the Categorical dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the Categorical dtype.

Examples

```
>>> is_categorical_dtype(object)
False
>>> is_categorical_dtype(CategoricalDtype())
True
>>> is_categorical_dtype([1, 2, 3])
False
>>> is_categorical_dtype(pd.Categorical([1, 2, 3]))
True
>>> is_categorical_dtype(pd.CategoricalIndex([1, 2, 3]))
True
```

pandas.api.types.is_complex_dtype

pandas.api.types.**is_complex_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of a complex dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of a complex dtype.

Examples

```
>>> is_complex_dtype(str)
False
>>> is_complex_dtype(int)
False
>>> is_complex_dtype(np.complex_)
True
>>> is_complex_dtype(np.array(['a', 'b']))
False
>>> is_complex_dtype(pd.Series([1, 2]))
False
>>> is_complex_dtype(np.array([1 + 1j, 5]))
True
```

pandas.api.types.is_datetime64_any_dtype

pandas.api.types.**is_datetime64_any_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of the datetime64 dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

bool Whether or not the array or dtype is of the datetime64 dtype.

Examples

```
>>> is_datetime64_any_dtype(str)
False
>>> is_datetime64_any_dtype(int)
False
>>> is_datetime64_any_dtype(np.datetime64)  # can be tz-naive
True
>>> is_datetime64_any_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_any_dtype(np.array(['a', 'b']))
False
>>> is_datetime64_any_dtype(np.array([1, 2]))
False
>>> is_datetime64_any_dtype(np.array([], dtype="datetime64[ns]"))
```

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```
True
>>> is_datetime64_any_dtype(pd.DatetimeIndex([1, 2, 3], dtype="datetime64[ns]"))
True
```

pandas.api.types.is_datetime64_dtype

pandas.api.types.**is_datetime64_dtype**(*arr_or_dtype*)

Check whether an array-like or dtype is of the datetime64 dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the datetime64 dtype.

Examples

```
>>> is_datetime64_dtype(object)
False
>>> is_datetime64_dtype(np.datetime64)
True
>>> is_datetime64_dtype(np.array([], dtype=int))
False
>>> is_datetime64_dtype(np.array([], dtype=np.datetime64))
True
>>> is_datetime64_dtype([1, 2, 3])
False
```

pandas.api.types.is_datetime64_ns_dtype

pandas.api.types.**is_datetime64_ns_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of the datetime64[ns] dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

bool Whether or not the array or dtype is of the datetime64[ns] dtype.

Examples

```
>>> is_datetime64_ns_dtype(str)
False
>>> is_datetime64_ns_dtype(int)
False
>>> is_datetime64_ns_dtype(np.datetime64)  # no unit
False
>>> is_datetime64_ns_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_ns_dtype(np.array(['a', 'b']))
```

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```
False
>>> is_datetime64_ns_dtype(np.array([1, 2]))
False
>>> is_datetime64_ns_dtype(np.array([], dtype="datetime64"))  # no unit
False
>>> is_datetime64_ns_dtype(np.array([], dtype="datetime64[ps]"))  # wrong unit
False
>>> is_datetime64_ns_dtype(pd.DatetimeIndex([1, 2, 3], dtype="datetime64[ns]"))
True
```

pandas.api.types.is_datetime64tz_dtype

pandas.api.types.**is_datetime64tz_dtype**(*arr_or_dtype*)

Check whether an array-like or dtype is of a DatetimeTZDtype dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of a DatetimeTZDtype dtype.

Examples

```
>>> is_datetime64tz_dtype(object)
False
>>> is_datetime64tz_dtype([1, 2, 3])
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3]))  # tz-naive
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
```

```
>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_datetime64tz_dtype(dtype)
True
>>> is_datetime64tz_dtype(s)
True
```

pandas.api.types.is_extension_type

pandas.api.types.**is_extension_type**(*arr*)

Check whether an array-like is of a pandas extension class instance.

Deprecated since version 1.0.0: Use `is_extension_array_dtype` instead.

Extension classes include categoricals, pandas sparse objects (i.e. classes represented within the pandas library and not ones external to it like scipy sparse matrices), and datetime-like arrays.

Parameters

arr [array-like] The array-like to check.

Returns

boolean Whether or not the array-like is of a pandas extension class instance.

Examples

```
>>> is_extension_type([1, 2, 3])
False
>>> is_extension_type(np.array([1, 2, 3]))
False
>>>
>>> cat = pd.Categorical([1, 2, 3])
>>>
>>> is_extension_type(cat)
True
>>> is_extension_type(pd.Series(cat))
True
>>> is_extension_type(pd.arrays.SparseArray([1, 2, 3]))
True
>>> from scipy.sparse import bsr_matrix
>>> is_extension_type(bsr_matrix([1, 2, 3]))
False
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3]))
False
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
>>>
>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_extension_type(s)
True
```

pandas.api.types.is_extension_array_dtype

pandas.api.types.**is_extension_array_dtype**(*arr_or_dtype*)

Check if an object is a pandas extension array type.

See the *Use Guide* for more.

Parameters

arr_or_dtype [object] For array-like input, the `.dtype` attribute will be extracted.

Returns

bool Whether the *arr_or_dtype* is an extension array type.

Notes

This checks whether an object implements the pandas extension array interface. In pandas, this includes:

- Categorical
- Sparse
- Interval
- Period
- DatetimeArray
- TimedeltaArray

Third-party libraries may implement arrays or types satisfying this interface as well.

Examples

```
>>> from pandas.api.types import is_extension_array_dtype
>>> arr = pd.Categorical(['a', 'b'])
>>> is_extension_array_dtype(arr)
True
>>> is_extension_array_dtype(arr.dtype)
True
```

```
>>> arr = np.array(['a', 'b'])
>>> is_extension_array_dtype(arr.dtype)
False
```

pandas.api.types.is_float_dtype

pandas.api.types.**is_float_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of a float dtype.

This function is internal and should not be exposed in the public API.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of a float dtype.

Examples

```
>>> is_float_dtype(str)
False
>>> is_float_dtype(int)
False
>>> is_float_dtype(float)
True
>>> is_float_dtype(np.array(['a', 'b']))
False
>>> is_float_dtype(pd.Series([1, 2]))
False
>>> is_float_dtype(pd.Index([1, 2.]))
True
```

pandas.api.types.is_int64_dtype

pandas.api.types.**is_int64_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of the int64 dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of the int64 dtype.

Notes

Depending on system architecture, the return value of *is_int64_dtype(int)* will be True if the OS uses 64-bit integers and False if the OS uses 32-bit integers.

Examples

```
>>> is_int64_dtype(str)
False
>>> is_int64_dtype(np.int32)
False
>>> is_int64_dtype(np.int64)
True
>>> is_int64_dtype('int8')
False
>>> is_int64_dtype('Int8')
False
>>> is_int64_dtype(pd.Int64Dtype)
True
>>> is_int64_dtype(float)
False
>>> is_int64_dtype(np.uint64)  # unsigned
False
>>> is_int64_dtype(np.array(['a', 'b']))
False
>>> is_int64_dtype(np.array([1, 2], dtype=np.int64))
True
>>> is_int64_dtype(pd.Index([1, 2.]))  # float
False
>>> is_int64_dtype(np.array([1, 2], dtype=np.uint32))  # unsigned
False
```

pandas.api.types.is_integer_dtype

pandas.api.types.**is_integer_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of an integer dtype.

Unlike in *in_any_int_dtype*, timedelta64 instances will return False.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. pandas.Int64Dtype) are also considered as integer by this function.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of an integer dtype and not an instance of timedelta64.

Examples

```
>>> is_integer_dtype(str)
False
>>> is_integer_dtype(int)
True
>>> is_integer_dtype(float)
False
>>> is_integer_dtype(np.uint64)
True
>>> is_integer_dtype('int8')
True
>>> is_integer_dtype('Int8')
True
>>> is_integer_dtype(pd.Int8Dtype)
True
>>> is_integer_dtype(np.datetime64)
False
>>> is_integer_dtype(np.timedelta64)
False
>>> is_integer_dtype(np.array(['a', 'b']))
False
>>> is_integer_dtype(pd.Series([1, 2]))
True
>>> is_integer_dtype(np.array([], dtype=np.timedelta64))
False
>>> is_integer_dtype(pd.Index([1, 2.]))  # float
False
```

pandas.api.types.is_interval_dtype

pandas.api.types.**is_interval_dtype**(*arr_or_dtype*)

Check whether an array-like or dtype is of the Interval dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the Interval dtype.

Examples

```
>>> is_interval_dtype(object)
False
>>> is_interval_dtype(IntervalDtype())
True
>>> is_interval_dtype([1, 2, 3])
False
>>>
>>> interval = pd.Interval(1, 2, closed="right")
>>> is_interval_dtype(interval)
False
>>> is_interval_dtype(pd.IntervalIndex([interval]))
True
```

pandas.api.types.is_numeric_dtype

pandas.api.types.**is_numeric_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of a numeric dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of a numeric dtype.

Examples

```
>>> is_numeric_dtype(str)
False
>>> is_numeric_dtype(int)
True
>>> is_numeric_dtype(float)
True
>>> is_numeric_dtype(np.uint64)
True
>>> is_numeric_dtype(np.datetime64)
False
>>> is_numeric_dtype(np.timedelta64)
False
>>> is_numeric_dtype(np.array(['a', 'b']))
False
>>> is_numeric_dtype(pd.Series([1, 2]))
True
>>> is_numeric_dtype(pd.Index([1, 2.]))
True
>>> is_numeric_dtype(np.array([], dtype=np.timedelta64))
False
```

pandas.api.types.is_object_dtype

pandas.api.types.**is_object_dtype**(*arr_or_dtype*)

Check whether an array-like or dtype is of the object dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the object dtype.

Examples

```
>>> is_object_dtype(object)
True
>>> is_object_dtype(int)
False
>>> is_object_dtype(np.array([], dtype=object))
True
>>> is_object_dtype(np.array([], dtype=int))
False
>>> is_object_dtype([1, 2, 3])
False
```

pandas.api.types.is_period_dtype

pandas.api.types.**is_period_dtype**(*arr_or_dtype*)

Check whether an array-like or dtype is of the Period dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the Period dtype.

Examples

```
>>> is_period_dtype(object)
False
>>> is_period_dtype(PeriodDtype(freq="D"))
True
>>> is_period_dtype([1, 2, 3])
False
>>> is_period_dtype(pd.Period("2017-01-01"))
False
>>> is_period_dtype(pd.PeriodIndex([], freq="A"))
True
```

pandas.api.types.is_signed_integer_dtype

pandas.api.types.**is_signed_integer_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of a signed integer dtype.

Unlike in *in_any_int_dtype*, timedelta64 instances will return False.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. pandas.Int64Dtype) are also considered as integer by this function.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of a signed integer dtype and not an instance of timedelta64.

Examples

```
>>> is_signed_integer_dtype(str)
False
>>> is_signed_integer_dtype(int)
True
>>> is_signed_integer_dtype(float)
False
>>> is_signed_integer_dtype(np.uint64)  # unsigned
False
>>> is_signed_integer_dtype('int8')
True
>>> is_signed_integer_dtype('Int8')
True
>>> is_signed_integer_dtype(pd.Int8Dtype)
True
>>> is_signed_integer_dtype(np.datetime64)
False
>>> is_signed_integer_dtype(np.timedelta64)
False
>>> is_signed_integer_dtype(np.array(['a', 'b']))
False
>>> is_signed_integer_dtype(pd.Series([1, 2]))
True
>>> is_signed_integer_dtype(np.array([], dtype=np.timedelta64))
False
>>> is_signed_integer_dtype(pd.Index([1, 2.]))  # float
False
>>> is_signed_integer_dtype(np.array([1, 2], dtype=np.uint32))  # unsigned
False
```

pandas.api.types.is_string_dtype

pandas.api.types.**is_string_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of the string dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of the string dtype.

Examples

```
>>> is_string_dtype(str)
True
>>> is_string_dtype(object)
True
>>> is_string_dtype(int)
False
>>>
>>> is_string_dtype(np.array(['a', 'b']))
True
```

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```
>>> is_string_dtype(pd.Series([1, 2]))
False
```

pandas.api.types.is_timedelta64_dtype

pandas.api.types.**is_timedelta64_dtype**(*arr_or_dtype*)

Check whether an array-like or dtype is of the timedelta64 dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the timedelta64 dtype.

Examples

```
>>> is_timedelta64_dtype(object)
False
>>> is_timedelta64_dtype(np.timedelta64)
True
>>> is_timedelta64_dtype([1, 2, 3])
False
>>> is_timedelta64_dtype(pd.Series([], dtype="timedelta64[ns]"))
True
>>> is_timedelta64_dtype('0 days')
False
```

pandas.api.types.is_timedelta64_ns_dtype

pandas.api.types.**is_timedelta64_ns_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of the timedelta64[ns] dtype.

This is a very specific dtype, so generic ones like *np.timedelta64* will return False if passed into this function.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of the timedelta64[ns] dtype.

Examples

```
>>> is_timedelta64_ns_dtype(np.dtype('m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.dtype('m8[ps]'))  # Wrong frequency
False
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype='m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype=np.timedelta64))
False
```

pandas.api.types.is_unsigned_integer_dtype

pandas.api.types.**is_unsigned_integer_dtype**(*arr_or_dtype*)

Check whether the provided array or dtype is of an unsigned integer dtype.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. pandas.UInt64Dtype) are also considered as integer by this function.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of an unsigned integer dtype.

Examples

```
>>> is_unsigned_integer_dtype(str)
False
>>> is_unsigned_integer_dtype(int)  # signed
False
>>> is_unsigned_integer_dtype(float)
False
>>> is_unsigned_integer_dtype(np.uint64)
True
>>> is_unsigned_integer_dtype('uint8')
True
>>> is_unsigned_integer_dtype('UInt8')
True
>>> is_unsigned_integer_dtype(pd.UInt8Dtype)
True
>>> is_unsigned_integer_dtype(np.array(['a', 'b']))
False
>>> is_unsigned_integer_dtype(pd.Series([1, 2]))  # signed
False
>>> is_unsigned_integer_dtype(pd.Index([1, 2.]))  # float
False
>>> is_unsigned_integer_dtype(np.array([1, 2], dtype=np.uint32))
True
```

pandas.api.types.is_sparse

pandas.api.types.**is_sparse**(*arr*)

Check whether an array-like is a 1-D pandas sparse array.

Check that the one-dimensional array-like is a pandas sparse array. Returns True if it is a pandas sparse array, not another type of sparse array.

Parameters

arr [array-like] Array-like to check.

Returns

bool Whether or not the array-like is a pandas sparse array.

Examples

Returns *True* if the parameter is a 1-D pandas sparse array.

```
>>> is_sparse(pd.arrays.SparseArray([0, 0, 1, 0]))
True
>>> is_sparse(pd.Series(pd.arrays.SparseArray([0, 0, 1, 0])))
True
```

Returns *False* if the parameter is not sparse.

```
>>> is_sparse(np.array([0, 0, 1, 0]))
False
>>> is_sparse(pd.Series([0, 1, 0, 0]))
False
```

Returns *False* if the parameter is not a pandas sparse array.

```
>>> from scipy.sparse import bsr_matrix
>>> is_sparse(bsr_matrix([0, 1, 0, 0]))
False
```

Returns *False* if the parameter has more than one dimension.

Iterable introspection

api.types.is_dict_like(obj)	Check if the object is dict-like.
api.types.is_file_like(obj)	Check if the object is a file-like object.
api.types.is_list_like	Check if the object is list-like.
api.types.is_named_tuple(obj)	Check if the object is a named tuple.
api.types.is_iterator	Check if the object is an iterator.

pandas.api.types.is_dict_like

pandas.api.types.**is_dict_like**(*obj*)

Check if the object is dict-like.

Parameters

obj [The object to check]

Returns

is_dict_like [bool] Whether *obj* has dict-like properties.

Examples

```
>>> is_dict_like({1: 2})
True
>>> is_dict_like([1, 2, 3])
False
>>> is_dict_like(dict)
False
>>> is_dict_like(dict())
True
```

pandas.api.types.is_file_like

pandas.api.types.**is_file_like**(*obj*)

Check if the object is a file-like object.

For objects to be considered file-like, they must be an iterator AND have either a *read* and/or *write* method as an attribute.

Note: file-like objects must be iterable, but iterable objects need not be file-like.

Parameters

obj [The object to check]

Returns

is_file_like [bool] Whether *obj* has file-like properties.

Examples

```
>>> import io
>>> buffer = io.StringIO("data")
>>> is_file_like(buffer)
True
>>> is_file_like([1, 2, 3])
False
```

pandas.api.types.is_list_like

pandas.api.types.**is_list_like**()

Check if the object is list-like.

Objects that are considered list-like are for example Python lists, tuples, sets, NumPy arrays, and Pandas Series.

Strings and datetime objects, however, are not considered list-like.

Parameters

obj [object] Object to check.

allow_sets [bool, default True] If this parameter is False, sets will not be considered list-like.

New in version 0.24.0.

Returns

bool Whether *obj* has list-like properties.

Examples

```
>>> is_list_like([1, 2, 3])
True
>>> is_list_like({1, 2, 3})
True
>>> is_list_like(datetime(2017, 1, 1))
False
>>> is_list_like("foo")
False
>>> is_list_like(1)
False
>>> is_list_like(np.array([2]))
True
>>> is_list_like(np.array(2))
False
```

pandas.api.types.is_named_tuple

pandas.api.types.**is_named_tuple**(*obj*)

Check if the object is a named tuple.

Parameters

obj [The object to check]

Returns

is_named_tuple [bool] Whether *obj* is a named tuple.

Examples

```
>>> from collections import namedtuple
>>> Point = namedtuple("Point", ["x", "y"])
>>> p = Point(1, 2)
>>>
>>> is_named_tuple(p)
True
>>> is_named_tuple((1, 2))
False
```

pandas.api.types.is_iterator

pandas.api.types.**is_iterator**()

Check if the object is an iterator.

This is intended for generators, not list-like objects.

Parameters

obj [The object to check]

Returns

is_iter [bool] Whether *obj* is an iterator.

Examples

```
>>> is_iterator((x for x in []))
True
>>> is_iterator([1, 2, 3])
False
>>> is_iterator(datetime(2017, 1, 1))
False
>>> is_iterator("foo")
False
>>> is_iterator(1)
False
```

Scalar introspection

api.types.is_bool	Return True if given object is boolean.
api.types.is_categorical(arr)	Check whether an array-like is a Categorical instance.
api.types.is_complex	Return True if given object is complex.
api.types.is_float	Return True if given object is float.
api.types.is_hashable(obj)	Return True if hash(obj) will succeed, False otherwise.
api.types.is_integer	Return True if given object is integer.
api.types.is_interval	
api.types.is_number(obj)	Check if the object is a number.
api.types.is_re(obj)	Check if the object is a regex pattern instance.
api.types.is_re_compilable(obj)	Check if the object can be compiled into a regex pattern instance.
api.types.is_scalar	Return True if given object is scalar.

pandas.api.types.is_bool

pandas.api.types.**is_bool**()
Return True if given object is boolean.

Returns

bool

pandas.api.types.is_categorical

pandas.api.types.**is_categorical**(*arr*)
Check whether an array-like is a Categorical instance.

Parameters

arr [array-like] The array-like to check.

Returns

boolean Whether or not the array-like is of a Categorical instance.

Examples

```
>>> is_categorical([1, 2, 3])
False
```

Categoricals, Series Categoricals, and CategoricalIndex will return True.

```
>>> cat = pd.Categorical([1, 2, 3])
>>> is_categorical(cat)
True
>>> is_categorical(pd.Series(cat))
True
>>> is_categorical(pd.CategoricalIndex([1, 2, 3]))
True
```

pandas.api.types.is_complex

pandas.api.types.**is_complex**()

Return True if given object is complex.

Returns

bool

pandas.api.types.is_float

pandas.api.types.**is_float**()

Return True if given object is float.

Returns

bool

pandas.api.types.is_hashable

pandas.api.types.**is_hashable**(*obj*)

Return True if hash(obj) will succeed, False otherwise.

Some types will pass a test against collections.abc.Hashable but fail when they are actually hashed with hash().

Distinguish between these and other types by trying the call to hash() and seeing if they raise TypeError.

Returns

bool

Examples

```
>>> import collections
>>> a = ([],)
>>> isinstance(a, collections.abc.Hashable)
True
>>> is_hashable(a)
False
```

pandas.api.types.is_integer

pandas.api.types.**is_integer**()

Return True if given object is integer.

Returns

bool

pandas.api.types.is_interval

pandas.api.types.**is_interval**()

pandas.api.types.is_number

pandas.api.types.**is_number**(*obj*)

Check if the object is a number.

Returns True when the object is a number, and False if is not.

Parameters

obj [any type] The object to check if is a number.

Returns

is_number [bool] Whether *obj* is a number or not.

See also:

api.types.is_integer Checks a subgroup of numbers.

Examples

```
>>> pd.api.types.is_number(1)
True
>>> pd.api.types.is_number(7.15)
True
```

Booleans are valid because they are int subclass.

```
>>> pd.api.types.is_number(False)
True
```

```
>>> pd.api.types.is_number("foo")
False
>>> pd.api.types.is_number("5")
False
```

pandas.api.types.is_re

pandas.api.types.**is_re**(*obj*)

Check if the object is a regex pattern instance.

Parameters

obj [The object to check]

Returns

is_regex [bool] Whether *obj* is a regex pattern.

Examples

```
>>> is_re(re.compile(".*"))
True
>>> is_re("foo")
False
```

pandas.api.types.is_re_compilable

pandas.api.types.**is_re_compilable**(*obj*)

Check if the object can be compiled into a regex pattern instance.

Parameters

obj [The object to check]

Returns

is_regex_compilable [bool] Whether *obj* can be compiled as a regex pattern.

Examples

```
>>> is_re_compilable(".*")
True
>>> is_re_compilable(1)
False
```

pandas.api.types.is_scalar

pandas.api.types.**is_scalar**()

Return True if given object is scalar.

Parameters

val [object] This includes:

- numpy array scalar (e.g. np.int64)
- Python builtin numerics
- Python builtin byte arrays and strings
- None
- datetime.datetime

- datetime.timedelta
- Period
- decimal.Decimal
- Interval
- DateOffset
- Fraction
- Number.

Returns

bool Return True if given object is scalar.

Examples

```
>>> dt = datetime.datetime(2018, 10, 3)
>>> pd.api.types.is_scalar(dt)
True
```

```
>>> pd.api.types.is_scalar([2, 3])
False
```

```
>>> pd.api.types.is_scalar({0: 1, 2: 3})
False
```

```
>>> pd.api.types.is_scalar((0, 2))
False
```

pandas supports PEP 3141 numbers:

```
>>> from fractions import Fraction
>>> pd.api.types.is_scalar(Fraction(3, 5))
True
```

3.14.5 Bug report function

show_versions([as_json])	Provide useful information, important for bug reports.

pandas.show_versions

pandas.**show_versions**(*as_json=False*)

Provide useful information, important for bug reports.

It comprises info about hosting operation system, pandas version, and versions of other installed relative packages.

Parameters

as_json [str or bool, default False]

- If False, outputs info in a human readable form to the console.

- If str, it will be considered as a path to a file. Info will be written to that file in JSON format.
- If True, outputs info in JSON format to the console.

3.15 Extensions

These are primarily intended for library authors looking to extend pandas objects.

api.extensions.register_extension_dtype(cls)	Register an ExtensionType with pandas as class decorator.
api.extensions.register_dataframe_accessor(name)	Register a custom accessor on DataFrame objects.
api.extensions.register_series_accessor(name)	Register a custom accessor on Series objects.
api.extensions.register_index_accessor(name)	Register a custom accessor on Index objects.
api.extensions.ExtensionDtype()	A custom data type, to be paired with an ExtensionArray.

3.15.1 pandas.api.extensions.register_extension_dtype

pandas.api.extensions.**register_extension_dtype**(*cls*)

Register an ExtensionType with pandas as class decorator.

New in version 0.24.0.

This enables operations like `.astype(name)` for the name of the ExtensionDtype.

Returns

callable A class decorator.

Examples

```
>>> from pandas.api.extensions import register_extension_dtype
>>> from pandas.api.extensions import ExtensionDtype
>>> @register_extension_dtype
... class MyExtensionDtype(ExtensionDtype):
...     name = "myextension"
```

3.15.2 pandas.api.extensions.register_dataframe_accessor

pandas.api.extensions.**register_dataframe_accessor**(*name*)

Register a custom accessor on DataFrame objects.

Parameters

name [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

Returns

callable A class decorator.

See also:

register_dataframe_accessor Register a custom accessor on DataFrame objects.
register_series_accessor Register a custom accessor on Series objects.

register_index_accessor Register a custom accessor on Index objects.

Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```
def __init__(self, pandas_object):  # noqa: E999
    ...
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your accessor has an incorrect dtype.

```
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

Examples

In your library code:

```
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:

```
In [1]: ds = pd.DataFrame({"longitude": np.linspace(0, 10),
   ...:                    "latitude": np.linspace(0, 20)})
In [2]: ds.geo.center
Out[2]: (5.0, 10.0)
In [3]: ds.geo.plot()  # plots data on a map
```

3.15.3 pandas.api.extensions.register_series_accessor

pandas.api.extensions.**register_series_accessor**(*name*)

Register a custom accessor on Series objects.

Parameters

name [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

Returns

callable A class decorator.

See also:

register_dataframe_accessor Register a custom accessor on DataFrame objects.
register_series_accessor Register a custom accessor on Series objects.
register_index_accessor Register a custom accessor on Index objects.

Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```
def __init__(self, pandas_object):  # noqa: E999
    ...
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your accessor has an incorrect dtype.

```
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

Examples

In your library code:

```
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:

```
In [1]: ds = pd.DataFrame({"longitude": np.linspace(0, 10),
   ...:                    "latitude": np.linspace(0, 20)})
In [2]: ds.geo.center
Out[2]: (5.0, 10.0)
In [3]: ds.geo.plot()  # plots data on a map
```

3.15.4 pandas.api.extensions.register_index_accessor

pandas.api.extensions.**register_index_accessor**(*name*)

Register a custom accessor on Index objects.

Parameters

name [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

Returns

callable A class decorator.

See also:

register_dataframe_accessor Register a custom accessor on DataFrame objects.
register_series_accessor Register a custom accessor on Series objects.
register_index_accessor Register a custom accessor on Index objects.

Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```
def __init__(self, pandas_object):  # noqa: E999
    ...
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your accessor has an incorrect dtype.

```
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

Examples

In your library code:

```
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
    def center(self):
        # return the geographic center point of this DataFrame
```

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```
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:

```
In [1]: ds = pd.DataFrame({"longitude": np.linspace(0, 10),
   ...:                    "latitude": np.linspace(0, 20)})
In [2]: ds.geo.center
Out[2]: (5.0, 10.0)
In [3]: ds.geo.plot()  # plots data on a map
```

3.15.5 pandas.api.extensions.ExtensionDtype

class pandas.api.extensions.**ExtensionDtype**

A custom data type, to be paired with an ExtensionArray.

See also:

extensions.register_extension_dtype Register an ExtensionType with pandas as class decorator.
extensions.ExtensionArray Abstract base class for custom 1-D array types.

Notes

The interface includes the following abstract methods that must be implemented by subclasses:

- type
- name

The following attributes and methods influence the behavior of the dtype in pandas operations

- _is_numeric
- _is_boolean
- _get_common_dtype

Optionally one can override construct_array_type for construction with the name of this dtype via the Registry. See `extensions.register_extension_dtype()`.

- construct_array_type

The *na_value* class attribute can be used to set the default NA value for this type. `numpy.nan` is used by default.

ExtensionDtypes are required to be hashable. The base class provides a default implementation, which relies on the `_metadata` class attribute. `_metadata` should be a tuple containing the strings that define your data type. For example, with `PeriodDtype` that's the `freq` attribute.

If you have a parametrized dtype you should set the ``_metadata`` class property.

Ideally, the attributes in `_metadata` will match the parameters to your `ExtensionDtype.__init__` (if any). If any of the attributes in `_metadata` don't implement the standard `__eq__` or `__hash__`, the default implementations here will not work.

Changed in version 0.24.0: Added `_metadata`, `__hash__`, and changed the default definition of `__eq__`.

For interaction with Apache Arrow (pyarrow), a `__from_arrow__` method can be implemented: this method receives a pyarrow Array or ChunkedArray as only argument and is expected to return the appropriate pandas

ExtensionArray for this dtype and the passed values:

```
class ExtensionDtype:

    def __from_arrow__(
        self, array: Union[pyarrow.Array, pyarrow.ChunkedArray]
    ) -> ExtensionArray:
        ...
```

This class does not inherit from 'abc.ABCMeta' for performance reasons. Methods and properties required by the interface raise `pandas.errors.AbstractMethodError` and no `register` method is provided for registering virtual subclasses.

Attributes

kind	A character code (one of 'biufcmMOSUV'), default 'O'
na_value	Default NA value to use for this type.
name	A string identifying the data type.
names	Ordered list of field names, or None if there are no fields.
type	The scalar type for the array, e.g.

pandas.api.extensions.ExtensionDtype.kind

property ExtensionDtype.**kind**

A character code (one of 'biufcmMOSUV'), default 'O'

This should match the NumPy dtype used when the array is converted to an ndarray, which is probably 'O' for object if the extension type cannot be represented as a built-in NumPy type.

See also:

numpy.dtype.kind

pandas.api.extensions.ExtensionDtype.na_value

property ExtensionDtype.**na_value**
Default NA value to use for this type.

This is used in e.g. ExtensionArray.take. This should be the user-facing "boxed" version of the NA value, not the physical NA value for storage. e.g. for JSONArray, this is an empty dictionary.

pandas.api.extensions.ExtensionDtype.name

property ExtensionDtype.**name**
A string identifying the data type.

Will be used for display in, e.g. `Series.dtype`

pandas.api.extensions.ExtensionDtype.names

property ExtensionDtype.**names**
Ordered list of field names, or None if there are no fields.

This is for compatibility with NumPy arrays, and may be removed in the future.

pandas.api.extensions.ExtensionDtype.type

property ExtensionDtype.**type**
The scalar type for the array, e.g. `int`

It's expected `ExtensionArray[item]` returns an instance of `ExtensionDtype.type` for scalar `item`, assuming that value is valid (not NA). NA values do not need to be instances of *type*.

Methods

construct_array_type()	Return the array type associated with this dtype.
construct_from_string(string)	Construct this type from a string.
is_dtype(dtype)	Check if we match 'dtype'.

pandas.api.extensions.ExtensionDtype.construct_array_type

classmethod ExtensionDtype.**construct_array_type**()
Return the array type associated with this dtype.

Returns

type

pandas.api.extensions.ExtensionDtype.construct_from_string

classmethod ExtensionDtype.**construct_from_string**(*string*)

Construct this type from a string.

This is useful mainly for data types that accept parameters. For example, a period dtype accepts a frequency parameter that can be set as `period[H]` (where H means hourly frequency).

By default, in the abstract class, just the name of the type is expected. But subclasses can overwrite this method to accept parameters.

Parameters

string [str] The name of the type, for example `category`.

Returns

ExtensionDtype Instance of the dtype.

Raises

TypeError If a class cannot be constructed from this 'string'.

Examples

For extension dtypes with arguments the following may be an adequate implementation.

```
>>> @classmethod
... def construct_from_string(cls, string):
...     pattern = re.compile(r"^my_type\[(?P<arg_name>.+)\]$")
...     match = pattern.match(string)
...     if match:
...         return cls(**match.groupdict())
...     else:
...         raise TypeError(
...             f"Cannot construct a '{cls.__name__}' from '{string}'"
...         )
```

pandas.api.extensions.ExtensionDtype.is_dtype

classmethod ExtensionDtype.**is_dtype**(*dtype*)

Check if we match 'dtype'.

Parameters

dtype [object] The object to check.

Returns

bool

Notes

The default implementation is True if

1. `cls.construct_from_string(dtype)` is an instance of `cls`.
2. `dtype` is an object and is an instance of `cls`
3. `dtype` has a `dtype` attribute, and any of the above conditions is true for `dtype.dtype`.

api.extensions.ExtensionArray()	Abstract base class for custom 1-D array types.
arrays.PandasArray(values[, copy])	A pandas ExtensionArray for NumPy data.

3.15.6 pandas.api.extensions.ExtensionArray

class pandas.api.extensions.**ExtensionArray**

Abstract base class for custom 1-D array types.

pandas will recognize instances of this class as proper arrays with a custom type and will not attempt to coerce them to objects. They may be stored directly inside a `DataFrame` or `Series`.

Notes

The interface includes the following abstract methods that must be implemented by subclasses:

- _from_sequence
- _from_factorized
- __getitem__
- __len__
- __eq__
- dtype
- nbytes
- isna
- take
- copy
- _concat_same_type

A default repr displaying the type, (truncated) data, length, and dtype is provided. It can be customized or replaced by by overriding:

- __repr__ : A default repr for the ExtensionArray.
- _formatter : Print scalars inside a Series or DataFrame.

Some methods require casting the ExtensionArray to an ndarray of Python objects with `self.astype(object)`, which may be expensive. When performance is a concern, we highly recommend overriding the following methods:

- fillna
- dropna
- unique
- factorize / _values_for_factorize
- argsort / _values_for_argsort
- searchsorted

The remaining methods implemented on this class should be performant, as they only compose abstract methods. Still, a more efficient implementation may be available, and these methods can be overridden.

One can implement methods to handle array reductions.

- _reduce

One can implement methods to handle parsing from strings that will be used in methods such as `pandas.io.parsers.read_csv`.

- _from_sequence_of_strings

This class does not inherit from 'abc.ABCMeta' for performance reasons. Methods and properties required by the interface raise `pandas.errors.AbstractMethodError` and no `register` method is provided for registering virtual subclasses.

ExtensionArrays are limited to 1 dimension.

They may be backed by none, one, or many NumPy arrays. For example, `pandas.Categorical` is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 address may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists. Pandas makes no assumptions on how the data are stored, just that it can be converted to a NumPy array. The ExtensionArray interface does not impose any rules on how this data is stored. However, currently, the backing data cannot be stored in attributes called `.values` or `._values` to ensure full compatibility with pandas internals. But other names as `.data`, `._data`, `._items`, ... can be freely used.

If implementing NumPy's `__array_ufunc__` interface, pandas expects that

1. You defer by returning `NotImplemented` when any Series are present in *inputs*. Pandas will extract the arrays and call the ufunc again.
2. You define a `_HANDLED_TYPES` tuple as an attribute on the class. Pandas inspect this to determine whether the ufunc is valid for the types present.

See *NumPy universal functions* for more.

By default, ExtensionArrays are not hashable. Immutable subclasses may override this behavior.

Attributes

dtype	An instance of 'ExtensionDtype'.
nbytes	The number of bytes needed to store this object in memory.
ndim	Extension Arrays are only allowed to be 1-dimensional.
shape	Return a tuple of the array dimensions.

pandas.api.extensions.ExtensionArray.dtype

property ExtensionArray.**dtype**

An instance of 'ExtensionDtype'.

pandas.api.extensions.ExtensionArray.nbytes

property ExtensionArray.**nbytes**
The number of bytes needed to store this object in memory.

pandas.api.extensions.ExtensionArray.ndim

property ExtensionArray.**ndim**
Extension Arrays are only allowed to be 1-dimensional.

pandas.api.extensions.ExtensionArray.shape

property ExtensionArray.**shape**
Return a tuple of the array dimensions.

Methods

argsort([ascending, kind, na_position])	Return the indices that would sort this array.
astype(dtype[, copy])	Cast to a NumPy array with 'dtype'.
copy()	Return a copy of the array.
dropna()	Return ExtensionArray without NA values.
factorize([na_sentinel])	Encode the extension array as an enumerated type.
fillna([value, method, limit])	Fill NA/NaN values using the specified method.
equals(other)	Return if another array is equivalent to this array.
isna()	A 1-D array indicating if each value is missing.
ravel([order])	Return a flattened view on this array.
repeat(repeats[, axis])	Repeat elements of a ExtensionArray.
searchsorted(value[, side, sorter])	Find indices where elements should be inserted to maintain order.
shift([periods, fill_value])	Shift values by desired number.
take(indices, *[, allow_fill, fill_value])	Take elements from an array.
unique()	Compute the ExtensionArray of unique values.
view([dtype])	Return a view on the array.
_concat_same_type(to_concat)	Concatenate multiple array of this dtype.
_formatter([boxed])	Formatting function for scalar values.
_from_factorized(values, original)	Reconstruct an ExtensionArray after factorization.
_from_sequence(scalars, *[, dtype, copy])	Construct a new ExtensionArray from a sequence of scalars.
_from_sequence_of_strings(strings, *[, ...])	Construct a new ExtensionArray from a sequence of strings.
_reduce(name, *[, skipna])	Return a scalar result of performing the reduction operation.
_values_for_argsort()	Return values for sorting.
_values_for_factorize()	Return an array and missing value suitable for factorization.

pandas.api.extensions.ExtensionArray.argsort

ExtensionArray.**argsort**(*ascending=True*, *kind='quicksort'*, *na_position='last'*, **args*, ***kwargs*)

Return the indices that would sort this array.

Parameters

ascending [bool, default True] Whether the indices should result in an ascending or descending sort.

kind [{'quicksort', 'mergesort', 'heapsort'}, optional] Sorting algorithm.

***args, **kwargs:** Passed through to `numpy.argsort()`.

Returns

ndarray Array of indices that sort `self`. If NaN values are contained, NaN values are placed at the end.

See also:

numpy.argsort Sorting implementation used internally.

pandas.api.extensions.ExtensionArray.astype

ExtensionArray.**astype**(*dtype*, *copy=True*)

Cast to a NumPy array with 'dtype'.

Parameters

dtype [str or dtype] Typecode or data-type to which the array is cast.

copy [bool, default True] Whether to copy the data, even if not necessary. If False, a copy is made only if the old dtype does not match the new dtype.

Returns

array [ndarray] NumPy ndarray with 'dtype' for its dtype.

pandas.api.extensions.ExtensionArray.copy

ExtensionArray.**copy**()

Return a copy of the array.

Returns

ExtensionArray

pandas.api.extensions.ExtensionArray.dropna

ExtensionArray.**dropna**()

Return ExtensionArray without NA values.

Returns

valid [ExtensionArray]

pandas.api.extensions.ExtensionArray.factorize

ExtensionArray.**factorize**(*na_sentinel=- 1*)

Encode the extension array as an enumerated type.

Parameters

na_sentinel [int, default -1] Value to use in the *codes* array to indicate missing values.

Returns

codes [ndarray] An integer NumPy array that's an indexer into the original ExtensionArray.

uniques [ExtensionArray] An ExtensionArray containing the unique values of *self*.

Note: uniques will *not* contain an entry for the NA value of the ExtensionArray if there are any missing values present in *self*.

See also:

factorize Top-level factorize method that dispatches here.

Notes

pandas.factorize() offers a *sort* keyword as well.

pandas.api.extensions.ExtensionArray.fillna

ExtensionArray.**fillna**(*value=None*, *method=None*, *limit=None*)

Fill NA/NaN values using the specified method.

Parameters

value [scalar, array-like] If a scalar value is passed it is used to fill all missing values. Alternatively, an array-like 'value' can be given. It's expected that the array-like have the same length as 'self'.

method [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap.

limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

Returns

ExtensionArray With NA/NaN filled.

pandas.api.extensions.ExtensionArray.equals

ExtensionArray.**equals**(*other*)

Return if another array is equivalent to this array.

Equivalent means that both arrays have the same shape and dtype, and all values compare equal. Missing values in the same location are considered equal (in contrast with normal equality).

Parameters

other [ExtensionArray] Array to compare to this Array.

Returns

boolean Whether the arrays are equivalent.

pandas.api.extensions.ExtensionArray.isna

ExtensionArray.**isna**()

A 1-D array indicating if each value is missing.

Returns

na_values [Union[np.ndarray, ExtensionArray]] In most cases, this should return a NumPy ndarray. For exceptional cases like `SparseArray`, where returning an ndarray would be expensive, an ExtensionArray may be returned.

Notes

If returning an ExtensionArray, then

- `na_values._is_boolean` should be True
- *na_values* should implement *ExtensionArray._reduce()*
- `na_values.any` and `na_values.all` should be implemented

pandas.api.extensions.ExtensionArray.ravel

ExtensionArray.**ravel**(*order='C'*)

Return a flattened view on this array.

Parameters

order [{None, 'C', 'F', 'A', 'K'}, default 'C']

Returns

ExtensionArray

Notes

- Because ExtensionArrays are 1D-only, this is a no-op.
- The "order" argument is ignored, is for compatibility with NumPy.

pandas.api.extensions.ExtensionArray.repeat

ExtensionArray.**repeat**(*repeats*, *axis=None*)

Repeat elements of a ExtensionArray.

Returns a new ExtensionArray where each element of the current ExtensionArray is repeated consecutively a given number of times.

Parameters

repeats [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty ExtensionArray.

axis [None] Must be `None`. Has no effect but is accepted for compatibility with numpy.

Returns

repeated_array [ExtensionArray] Newly created ExtensionArray with repeated elements.

See also:

`Series.repeat` Equivalent function for Series.

`Index.repeat` Equivalent function for Index.

`numpy.repeat` Similar method for `numpy.ndarray`.

`ExtensionArray.take` Take arbitrary positions.

Examples

```
>>> cat = pd.Categorical(['a', 'b', 'c'])
>>> cat
['a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
>>> cat.repeat(2)
['a', 'a', 'b', 'b', 'c', 'c']
Categories (3, object): ['a', 'b', 'c']
>>> cat.repeat([1, 2, 3])
['a', 'b', 'b', 'c', 'c', 'c']
Categories (3, object): ['a', 'b', 'c']
```

pandas.api.extensions.ExtensionArray.searchsorted

ExtensionArray.**searchsorted**(*value*, *side='left'*, *sorter=None*)

Find indices where elements should be inserted to maintain order.

New in version 0.24.0.

Find the indices into a sorted array *self* (a) such that, if the corresponding elements in *value* were inserted before the indices, the order of *self* would be preserved.

Assuming that *self* is sorted:

side	returned index *i* satisfies
left	`self[i-1] < value <= self[i]`
right	`self[i-1] <= value < self[i]`

Parameters

value [array_like] Values to insert into *self*.

side [{'left', 'right'}, optional] If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *self*).

sorter [1-D array_like, optional] Optional array of integer indices that sort array a into ascending order. They are typically the result of argsort.

Returns

array of ints Array of insertion points with the same shape as *value*.

See also:

`numpy.searchsorted` Similar method from NumPy.

pandas.api.extensions.ExtensionArray.shift

ExtensionArray.**shift**(*periods=1*, *fill_value=None*)

Shift values by desired number.

Newly introduced missing values are filled with `self.dtype.na_value`.

New in version 0.24.0.

Parameters

periods [int, default 1] The number of periods to shift. Negative values are allowed for shifting backwards.

fill_value [object, optional] The scalar value to use for newly introduced missing values. The default is `self.dtype.na_value`.

New in version 0.24.0.

Returns

ExtensionArray Shifted.

Notes

If `self` is empty or `periods` is 0, a copy of `self` is returned.

If `periods > len(self)`, then an array of size len(self) is returned, with all values filled with `self.dtype.na_value`.

pandas.api.extensions.ExtensionArray.take

`ExtensionArray.`**`take`**(*indices*, *, *allow_fill=False*, *fill_value=None*)

Take elements from an array.

Parameters

indices [sequence of int] Indices to be taken.

allow_fill [bool, default False] How to handle negative values in *indices*.

- False: negative values in *indices* indicate positional indices from the right (the default). This is similar to `numpy.take()`.
- True: negative values in *indices* indicate missing values. These values are set to *fill_value*. Any other other negative values raise a `ValueError`.

fill_value [any, optional] Fill value to use for NA-indices when *allow_fill* is True. This may be `None`, in which case the default NA value for the type, `self.dtype.na_value`, is used.

For many ExtensionArrays, there will be two representations of *fill_value*: a user-facing "boxed" scalar, and a low-level physical NA value. *fill_value* should be the user-facing version, and the implementation should handle translating that to the physical version for processing the take if necessary.

Returns

ExtensionArray

Raises

IndexError When the indices are out of bounds for the array.

ValueError When *indices* contains negative values other than `-1` and *allow_fill* is True.

See also:

`numpy.take` Take elements from an array along an axis.

`api.extensions.take` Take elements from an array.

Notes

ExtensionArray.take is called by `Series.__getitem__`, `.loc`, `iloc`, when *indices* is a sequence of values. Additionally, it's called by `Series.reindex()`, or any other method that causes realignment, with a *fill_value*.

Examples

Here's an example implementation, which relies on casting the extension array to object dtype. This uses the helper method `pandas.api.extensions.take()`.

```
def take(self, indices, allow_fill=False, fill_value=None):
    from pandas.core.algorithms import take

    # If the ExtensionArray is backed by an ndarray, then
    # just pass that here instead of coercing to object.
    data = self.astype(object)

    if allow_fill and fill_value is None:
        fill_value = self.dtype.na_value

    # fill value should always be translated from the scalar
    # type for the array, to the physical storage type for
    # the data, before passing to take.

    result = take(data, indices, fill_value=fill_value,
                  allow_fill=allow_fill)
    return self._from_sequence(result, dtype=self.dtype)
```

pandas.api.extensions.ExtensionArray.unique

ExtensionArray.**unique**()

Compute the ExtensionArray of unique values.

Returns

uniques [ExtensionArray]

pandas.api.extensions.ExtensionArray.view

ExtensionArray.**view**(*dtype=None*)

Return a view on the array.

Parameters

dtype [str, np.dtype, or ExtensionDtype, optional] Default None.

Returns

ExtensionArray or np.ndarray A view on the *ExtensionArray*'s data.

pandas.api.extensions.ExtensionArray._concat_same_type

classmethod ExtensionArray.**_concat_same_type**(*to_concat*)

Concatenate multiple array of this dtype.

Parameters

to_concat [sequence of this type]

Returns

ExtensionArray

pandas.api.extensions.ExtensionArray._formatter

ExtensionArray.**_formatter**(*boxed=False*)
Formatting function for scalar values.

This is used in the default '__repr__'. The returned formatting function receives instances of your scalar type.

Parameters

boxed [bool, default False] An indicated for whether or not your array is being printed within a Series, DataFrame, or Index (True), or just by itself (False). This may be useful if you want scalar values to appear differently within a Series versus on its own (e.g. quoted or not).

Returns

Callable[[Any], str] A callable that gets instances of the scalar type and returns a string. By default, `repr()` is used when `boxed=False` and `str()` is used when `boxed=True`.

pandas.api.extensions.ExtensionArray._from_factorized

classmethod ExtensionArray.**_from_factorized**(*values*, *original*)
Reconstruct an ExtensionArray after factorization.

Parameters

values [ndarray] An integer ndarray with the factorized values.

original [ExtensionArray] The original ExtensionArray that factorize was called on.

See also:

factorize Top-level factorize method that dispatches here.

ExtensionArray.factorize Encode the extension array as an enumerated type.

pandas.api.extensions.ExtensionArray._from_sequence

classmethod ExtensionArray.**_from_sequence**(*scalars*, ***, *dtype=None*, *copy=False*)
Construct a new ExtensionArray from a sequence of scalars.

Parameters

scalars [Sequence] Each element will be an instance of the scalar type for this array, `cls.dtype.type` or be converted into this type in this method.

dtype [dtype, optional] Construct for this particular dtype. This should be a Dtype compatible with the ExtensionArray.

copy [bool, default False] If True, copy the underlying data.

Returns

ExtensionArray

pandas.api.extensions.ExtensionArray._from_sequence_of_strings

classmethod ExtensionArray.**_from_sequence_of_strings**(*strings*, ***, *dtype=None*, *copy=False*)

Construct a new ExtensionArray from a sequence of strings.

New in version 0.24.0.

Parameters

strings [Sequence] Each element will be an instance of the scalar type for this array, `cls.dtype.type`.

dtype [dtype, optional] Construct for this particular dtype. This should be a Dtype compatible with the ExtensionArray.

copy [bool, default False] If True, copy the underlying data.

Returns

ExtensionArray

pandas.api.extensions.ExtensionArray._reduce

ExtensionArray.**_reduce**(*name*, ***, *skipna=True*, ***kwargs*)

Return a scalar result of performing the reduction operation.

Parameters

name [str] Name of the function, supported values are: { any, all, min, max, sum, mean, median, prod, std, var, sem, kurt, skew }.

skipna [bool, default True] If True, skip NaN values.

****kwargs** Additional keyword arguments passed to the reduction function. Currently, *ddof* is the only supported kwarg.

Returns

scalar

Raises

TypeError [subclass does not define reductions]

pandas.api.extensions.ExtensionArray._values_for_argsort

ExtensionArray.**_values_for_argsort**()

Return values for sorting.

Returns

ndarray The transformed values should maintain the ordering between values within the array.

See also:

ExtensionArray.argsort Return the indices that would sort this array.

pandas.api.extensions.ExtensionArray._values_for_factorize

ExtensionArray.**_values_for_factorize**()
Return an array and missing value suitable for factorization.

Returns

values [ndarray] An array suitable for factorization. This should maintain order and be a supported dtype (Float64, Int64, UInt64, String, Object). By default, the extension array is cast to object dtype.

na_value [object] The value in *values* to consider missing. This will be treated as NA in the factorization routines, so it will be coded as *na_sentinel* and not included in *uniques*. By default, `np.nan` is used.

Notes

The values returned by this method are also used in *pandas.util.hash_pandas_object()*.

3.15.7 pandas.arrays.PandasArray

class pandas.arrays.**PandasArray**(*values*, *copy=False*)
A pandas ExtensionArray for NumPy data.

New in version 0.24.0.

This is mostly for internal compatibility, and is not especially useful on its own.

Parameters

values [ndarray] The NumPy ndarray to wrap. Must be 1-dimensional.

copy [bool, default False] Whether to copy *values*.

Attributes

None	

Methods

None	

Additionally, we have some utility methods for ensuring your object behaves correctly.

api.indexers.check_array_indexer(array, indexer)	Check if *indexer* is a valid array indexer for *array*.

3.15.8 pandas.api.indexers.check_array_indexer

pandas.api.indexers.**check_array_indexer**(*array*, *indexer*)

Check if *indexer* is a valid array indexer for *array*.

For a boolean mask, *array* and *indexer* are checked to have the same length. The dtype is validated, and if it is an integer or boolean ExtensionArray, it is checked if there are missing values present, and it is converted to the appropriate numpy array. Other dtypes will raise an error.

Non-array indexers (integer, slice, Ellipsis, tuples, ..) are passed through as is.

New in version 1.0.0.

Parameters

array [array-like] The array that is being indexed (only used for the length).

indexer [array-like or list-like] The array-like that's used to index. List-like input that is not yet a numpy array or an ExtensionArray is converted to one. Other input types are passed through as is.

Returns

numpy.ndarray The validated indexer as a numpy array that can be used to index.

Raises

IndexError When the lengths don't match.

ValueError When *indexer* cannot be converted to a numpy ndarray to index (e.g. presence of missing values).

See also:

api.types.is_bool_dtype Check if *key* is of boolean dtype.

Examples

When checking a boolean mask, a boolean ndarray is returned when the arguments are all valid.

```
>>> mask = pd.array([True, False])
>>> arr = pd.array([1, 2])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([ True, False])
```

An IndexError is raised when the lengths don't match.

```
>>> mask = pd.array([True, False, True])
>>> pd.api.indexers.check_array_indexer(arr, mask)
Traceback (most recent call last):
...
IndexError: Boolean index has wrong length: 3 instead of 2.
```

NA values in a boolean array are treated as False.

```
>>> mask = pd.array([True, pd.NA])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([ True, False])
```

A numpy boolean mask will get passed through (if the length is correct):

```
>>> mask = np.array([True, False])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([ True, False])
```

Similarly for integer indexers, an integer ndarray is returned when it is a valid indexer, otherwise an error is (for integer indexers, a matching length is not required):

```
>>> indexer = pd.array([0, 2], dtype="Int64")
>>> arr = pd.array([1, 2, 3])
>>> pd.api.indexers.check_array_indexer(arr, indexer)
array([0, 2])
```

```
>>> indexer = pd.array([0, pd.NA], dtype="Int64")
>>> pd.api.indexers.check_array_indexer(arr, indexer)
Traceback (most recent call last):
...
ValueError: Cannot index with an integer indexer containing NA values
```

For non-integer/boolean dtypes, an appropriate error is raised:

```
>>> indexer = np.array([0., 2.], dtype="float64")
>>> pd.api.indexers.check_array_indexer(arr, indexer)
Traceback (most recent call last):
...
IndexError: arrays used as indices must be of integer or boolean type
```

The sentinel `pandas.api.extensions.no_default` is used as the default value in some methods. Use an `is` comparison to check if the user provides a non-default value.

CHAPTER

FOUR

DEVELOPMENT

4.1 Contributing to pandas

Table of contents:

- *Where to start?*
- *Bug reports and enhancement requests*
- *Working with the code*
  - *Version control, Git, and GitHub*
  - *Getting started with Git*
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    - *Using a Docker container*
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- *Contributing to the code base*
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        - *C (cpplint)*
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    - *Documenting your code*
- *Contributing your changes to pandas*
    - *Committing your code*
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    - *Review your code*
    - *Finally, make the pull request*
    - *Updating your pull request*
    - *Delete your merged branch (optional)*
- *Tips for a successful pull request*

4.1.1 Where to start?

All contributions, bug reports, bug fixes, documentation improvements, enhancements, and ideas are welcome.

If you are brand new to pandas or open-source development, we recommend going through the GitHub "issues" tab to find issues that interest you. There are a number of issues listed under Docs and good first issue where you could start out. Once you've found an interesting issue, you can return here to get your development environment setup.

When you start working on an issue, it's a good idea to assign the issue to yourself, so nobody else duplicates the work on it. GitHub restricts assigning issues to maintainers of the project only. In most projects, and until recently in pandas, contributors added a comment letting others know they are working on an issue. While this is ok, you need to check each issue individually, and it's not possible to find the unassigned ones.

For this reason, we implemented a workaround consisting of adding a comment with the exact text `take`. When you

do it, a GitHub action will automatically assign you the issue (this will take seconds, and may require refreshing the page to see it). By doing this, it's possible to filter the list of issues and find only the unassigned ones.

So, a good way to find an issue to start contributing to pandas is to check the list of unassigned good first issues and assign yourself one you like by writing a comment with the exact text `take`.

If for whatever reason you are not able to continue working with the issue, please try to unassign it, so other people know it's available again. You can check the list of assigned issues, since people may not be working in them anymore. If you want to work on one that is assigned, feel free to kindly ask the current assignee if you can take it (please allow at least a week of inactivity before considering work in the issue discontinued).

Feel free to ask questions on the mailing list or on Gitter.

4.1.2 Bug reports and enhancement requests

Bug reports are an important part of making pandas more stable. Having a complete bug report will allow others to reproduce the bug and provide insight into fixing. See this stackoverflow article and this blogpost for tips on writing a good bug report.

Trying the bug-producing code out on the *master* branch is often a worthwhile exercise to confirm the bug still exists. It is also worth searching existing bug reports and pull requests to see if the issue has already been reported and/or fixed.

Bug reports must:

1. Include a short, self-contained Python snippet reproducing the problem. You can format the code nicely by using GitHub Flavored Markdown:

```
```python
>>> from pandas import DataFrame
>>> df = DataFrame(...)
...
```
```

2. Include the full version string of pandas and its dependencies. You can use the built-in function:

```
>>> import pandas as pd
>>> pd.show_versions()
```

3. Explain why the current behavior is wrong/not desired and what you expect instead.

The issue will then show up to the pandas community and be open to comments/ideas from others.

4.1.3 Working with the code

Now that you have an issue you want to fix, enhancement to add, or documentation to improve, you need to learn how to work with GitHub and the pandas code base.

Version control, Git, and GitHub

To the new user, working with Git is one of the more daunting aspects of contributing to pandas. It can very quickly become overwhelming, but sticking to the guidelines below will help keep the process straightforward and mostly trouble free. As always, if you are having difficulties please feel free to ask for help.

The code is hosted on GitHub. To contribute you will need to sign up for a free GitHub account. We use Git for version control to allow many people to work together on the project.

Some great resources for learning Git:

- the GitHub help pages.
- the NumPy's documentation.
- Matthew Brett's Pydagogue.

Getting started with Git

GitHub has instructions for installing git, setting up your SSH key, and configuring git. All these steps need to be completed before you can work seamlessly between your local repository and GitHub.

Forking

You will need your own fork to work on the code. Go to the pandas project page and hit the `Fork` button. You will want to clone your fork to your machine:

```
git clone https://github.com/your-user-name/pandas.git pandas-yourname
cd pandas-yourname
git remote add upstream https://github.com/pandas-dev/pandas.git
```

This creates the directory `pandas-yourname` and connects your repository to the upstream (main project) *pandas* repository.

Note that performing a shallow clone (with `--depth==N`, for some `N` greater or equal to 1) might break some tests and features as `pd.show_versions()` as the version number cannot be computed anymore.

Creating a development environment

To test out code changes, you'll need to build pandas from source, which requires a C/C++ compiler and Python environment. If you're making documentation changes, you can skip to *Contributing to the documentation* but if you skip creating the development environment you won't be able to build the documentation locally before pushing your changes.

Using a Docker container

Instead of manually setting up a development environment, you can use Docker to automatically create the environment with just several commands. pandas provides a `DockerFile` in the root directory to build a Docker image with a full pandas development environment.

Docker Commands

Pass your GitHub username in the `DockerFile` to use your own fork:

```
# Build the image pandas-yourname-env
docker build --tag pandas-yourname-env .
# Run a container and bind your local forked repo, pandas-yourname, to the container
docker run -it --rm -v path-to-pandas-yourname:/home/pandas-yourname pandas-yourname-
↪env
```

Even easier, you can integrate Docker with the following IDEs:

Visual Studio Code

You can use the DockerFile to launch a remote session with Visual Studio Code, a popular free IDE, using the `.devcontainer.json` file. See https://code.visualstudio.com/docs/remote/containers for details.

PyCharm (Professional)

Enable Docker support and use the Services tool window to build and manage images as well as run and interact with containers. See https://www.jetbrains.com/help/pycharm/docker.html for details.

Note that you might need to rebuild the C extensions if/when you merge with upstream/master using:

```
python setup.py build_ext -j 4
```

Installing a C compiler

pandas uses C extensions (mostly written using Cython) to speed up certain operations. To install pandas from source, you need to compile these C extensions, which means you need a C compiler. This process depends on which platform you're using.

If you have setup your environment using `conda`, the packages `c-compiler` and `cxx-compiler` will install a fitting compiler for your platform that is compatible with the remaining conda packages. On Windows and macOS, you will also need to install the SDKs as they have to be distributed separately. These packages will be automatically installed by using `pandas`'s `environment.yml`.

Windows

You will need Build Tools for Visual Studio 2017.

> **Warning:** You DO NOT need to install Visual Studio 2019. You only need "Build Tools for Visual Studio 2019" found by scrolling down to "All downloads" -> "Tools for Visual Studio 2019". In the installer, select the "C++ build tools" workload.

You can install the necessary components on the commandline using vs_buildtools.exe:

```
vs_buildtools.exe --quiet --wait --norestart --nocache ^
    --installPath C:\BuildTools ^
    --add "Microsoft.VisualStudio.Workload.VCTools;includeRecommended" ^
    --add Microsoft.VisualStudio.Component.VC.v141 ^
    --add Microsoft.VisualStudio.Component.VC.v141.x86.x64 ^
    --add Microsoft.VisualStudio.Component.Windows10SDK.17763
```

To setup the right paths on the commandline, call `"C:\BuildTools\VC\Auxiliary\Build\vcvars64.bat" -vcvars_ver=14.16 10.0.17763.0`.

macOS

To use the `conda`-based compilers, you will need to install the Developer Tools using `xcode-select --install`. Otherwise information about compiler installation can be found here: https://devguide.python.org/setup/#macos

Linux

For Linux-based `conda` installations, you won't have to install any additional components outside of the conda environment. The instructions below are only needed if your setup isn't based on conda environments.

Some Linux distributions will come with a pre-installed C compiler. To find out which compilers (and versions) are installed on your system:

```
# for Debian/Ubuntu:
dpkg --list | grep compiler
# for Red Hat/RHEL/CentOS/Fedora:
yum list installed | grep -i --color compiler
```

GCC (GNU Compiler Collection), is a widely used compiler, which supports C and a number of other languages. If GCC is listed as an installed compiler nothing more is required. If no C compiler is installed (or you wish to install a newer version) you can install a compiler (GCC in the example code below) with:

```
# for recent Debian/Ubuntu:
sudo apt install build-essential
# for Red Had/RHEL/CentOS/Fedora
yum groupinstall "Development Tools"
```

For other Linux distributions, consult your favourite search engine for compiler installation instructions.

Let us know if you have any difficulties by opening an issue or reaching out on Gitter.

Creating a Python environment

Now create an isolated pandas development environment:

- Install either Anaconda, miniconda, or miniforge
- Make sure your conda is up to date (`conda update conda`)
- Make sure that you have *cloned the repository*
- `cd` to the pandas source directory

We'll now kick off a three-step process:

1. Install the build dependencies
2. Build and install pandas
3. Install the optional dependencies

```
# Create and activate the build environment
conda env create -f environment.yml
conda activate pandas-dev

# or with older versions of Anaconda:
source activate pandas-dev

# Build and install pandas
python setup.py build_ext -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517
```

At this point you should be able to import pandas from your locally built version:

```
$ python  # start an interpreter
>>> import pandas
>>> print(pandas.__version__)
0.22.0.dev0+29.g4ad6d4d74
```

This will create the new environment, and not touch any of your existing environments, nor any existing Python installation.

To view your environments:

```
conda info -e
```

To return to your root environment:

```
conda deactivate
```

See the full conda docs here.

Creating a Python environment (pip)

If you aren't using conda for your development environment, follow these instructions. You'll need to have at least Python 3.6.1 installed on your system.

Unix/macOS with virtualenv

```
# Create a virtual environment
# Use an ENV_DIR of your choice. We'll use ~/virtualenvs/pandas-dev
# Any parent directories should already exist
python3 -m venv ~/virtualenvs/pandas-dev

# Activate the virtualenv
. ~/virtualenvs/pandas-dev/bin/activate

# Install the build dependencies
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517
```

Unix/macOS with pyenv

Consult the docs for setting up pyenv here.

```
# Create a virtual environment
# Use an ENV_DIR of your choice. We'll use ~/Users/<yourname>/.pyenv/versions/pandas-
↪dev

pyenv virtualenv <version> <name-to-give-it>

# For instance:
pyenv virtualenv 3.7.6 pandas-dev

# Activate the virtualenv
pyenv activate pandas-dev
```

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```
# Now install the build dependencies in the cloned pandas repo
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517
```

Windows

Below is a brief overview on how to set-up a virtual environment with Powershell under Windows. For details please refer to the official virtualenv user guide

Use an ENV_DIR of your choice. We'll use ~\virtualenvs\pandas-dev where '~' is the folder pointed to by either $env:USERPROFILE (Powershell) or %USERPROFILE% (cmd.exe) environment variable. Any parent directories should already exist.

```
# Create a virtual environment
python -m venv $env:USERPROFILE\virtualenvs\pandas-dev

# Activate the virtualenv. Use activate.bat for cmd.exe
~\virtualenvs\pandas-dev\Scripts\Activate.ps1

# Install the build dependencies
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517
```

Creating a branch

You want your master branch to reflect only production-ready code, so create a feature branch for making your changes. For example:

```
git branch shiny-new-feature
git checkout shiny-new-feature
```

The above can be simplified to:

```
git checkout -b shiny-new-feature
```

This changes your working directory to the shiny-new-feature branch. Keep any changes in this branch specific to one bug or feature so it is clear what the branch brings to pandas. You can have many shiny-new-features and switch in between them using the git checkout command.

When creating this branch, make sure your master branch is up to date with the latest upstream master version. To update your local master branch, you can do:

```
git checkout master
git pull upstream master --ff-only
```

When you want to update the feature branch with changes in master after you created the branch, check the section on *updating a PR*.

4.1.4 Contributing to the documentation

Contributing to the documentation benefits everyone who uses pandas. We encourage you to help us improve the documentation, and you don't have to be an expert on pandas to do so! In fact, there are sections of the docs that are worse off after being written by experts. If something in the docs doesn't make sense to you, updating the relevant section after you figure it out is a great way to ensure it will help the next person.

Documentation:

- *About the pandas documentation*
- *Updating a pandas docstring*
- *How to build the pandas documentation*
  - *Requirements*
  - *Building the documentation*
  - *Building master branch documentation*

About the pandas documentation

The documentation is written in **reStructuredText**, which is almost like writing in plain English, and built using Sphinx. The Sphinx Documentation has an excellent introduction to reST. Review the Sphinx docs to perform more complex changes to the documentation as well.

Some other important things to know about the docs:

- The pandas documentation consists of two parts: the docstrings in the code itself and the docs in this folder `doc/`.

  The docstrings provide a clear explanation of the usage of the individual functions, while the documentation in this folder consists of tutorial-like overviews per topic together with some other information (what's new, installation, etc).

- The docstrings follow a pandas convention, based on the **Numpy Docstring Standard**. Follow the *pandas docstring guide* for detailed instructions on how to write a correct docstring.

pandas docstring guide

About docstrings and standards

A Python docstring is a string used to document a Python module, class, function or method, so programmers can understand what it does without having to read the details of the implementation.

Also, it is a common practice to generate online (html) documentation automatically from docstrings. Sphinx serves this purpose.

The next example gives an idea of what a docstring looks like:

```
def add(num1, num2):
    """
    Add up two integer numbers.

    This function simply wraps the ``+`` operator, and does not
```

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```
    do anything interesting, except for illustrating what
    the docstring of a very simple function looks like.

    Parameters
    ----------
    num1 : int
        First number to add.
    num2 : int
        Second number to add.

    Returns
    -------
    int
        The sum of ``num1`` and ``num2``.

    See Also
    --------
    subtract : Subtract one integer from another.

    Examples
    --------
    >>> add(2, 2)
    4
    >>> add(25, 0)
    25
    >>> add(10, -10)
    0
    """
    return num1 + num2
```

Some standards regarding docstrings exist, which make them easier to read, and allow them be easily exported to other formats such as html or pdf.

The first conventions every Python docstring should follow are defined in PEP-257.

As PEP-257 is quite broad, other more specific standards also exist. In the case of pandas, the NumPy docstring convention is followed. These conventions are explained in this document:

- numpydoc docstring guide (which is based in the original Guide to NumPy/SciPy documentation)

numpydoc is a Sphinx extension to support the NumPy docstring convention.

The standard uses reStructuredText (reST). reStructuredText is a markup language that allows encoding styles in plain text files. Documentation about reStructuredText can be found in:

- Sphinx reStructuredText primer
- Quick reStructuredText reference
- Full reStructuredText specification

pandas has some helpers for sharing docstrings between related classes, see *Sharing docstrings*.

The rest of this document will summarize all the above guidelines, and will provide additional conventions specific to the pandas project.

Writing a docstring

General rules

Docstrings must be defined with three double-quotes. No blank lines should be left before or after the docstring. The text starts in the next line after the opening quotes. The closing quotes have their own line (meaning that they are not at the end of the last sentence).

On rare occasions reST styles like bold text or italics will be used in docstrings, but is it common to have inline code, which is presented between backticks. The following are considered inline code:

- The name of a parameter
- Python code, a module, function, built-in, type, literal... (e.g. `os`, `list`, `numpy.abs`, `datetime.date`, `True`)
- A pandas class (in the form `:class:`pandas.Series``)
- A pandas method (in the form `:meth:`pandas.Series.sum``)
- A pandas function (in the form `:func:`pandas.to_datetime``)

Note: To display only the last component of the linked class, method or function, prefix it with ~. For example, `:class:`~pandas.Series`` will link to `pandas.Series` but only display the last part, `Series` as the link text. See Sphinx cross-referencing syntax for details.

Good:

```
def add_values(arr):
    """
    Add the values in ``arr``.

    This is equivalent to Python ``sum`` of :meth:`pandas.Series.sum`.

    Some sections are omitted here for simplicity.
    """
    return sum(arr)
```

Bad:

```
def func():

    """Some function.

    With several mistakes in the docstring.

    It has a blank like after the signature ``def func():``.

    The text 'Some function' should go in the line after the
    opening quotes of the docstring, not in the same line.

    There is a blank line between the docstring and the first line
    of code ``foo = 1``.

    The closing quotes should be in the next line, not in this one."""

    foo = 1
```

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```
    bar = 2
    return foo + bar
```

Section 1: short summary

The short summary is a single sentence that expresses what the function does in a concise way.

The short summary must start with a capital letter, end with a dot, and fit in a single line. It needs to express what the object does without providing details. For functions and methods, the short summary must start with an infinitive verb.

Good:

```
def astype(dtype):
    """
    Cast Series type.

    This section will provide further details.
    """
    pass
```

Bad:

```
def astype(dtype):
    """
    Casts Series type.

    Verb in third-person of the present simple, should be infinitive.
    """
    pass
```

```
def astype(dtype):
    """
    Method to cast Series type.

    Does not start with verb.
    """
    pass
```

```
def astype(dtype):
    """
    Cast Series type

    Missing dot at the end.
    """
    pass
```

```
def astype(dtype):
    """
    Cast Series type from its current type to the new type defined in
    the parameter dtype.

    Summary is too verbose and doesn't fit in a single line.
    """
    pass
```

Section 2: extended summary

The extended summary provides details on what the function does. It should not go into the details of the parameters, or discuss implementation notes, which go in other sections.

A blank line is left between the short summary and the extended summary. Every paragraph in the extended summary ends with a dot.

The extended summary should provide details on why the function is useful and their use cases, if it is not too generic.

```
def unstack():
    """
    Pivot a row index to columns.

    When using a MultiIndex, a level can be pivoted so each value in
    the index becomes a column. This is especially useful when a subindex
    is repeated for the main index, and data is easier to visualize as a
    pivot table.

    The index level will be automatically removed from the index when added
    as columns.
    """
    pass
```

Section 3: parameters

The details of the parameters will be added in this section. This section has the title "Parameters", followed by a line with a hyphen under each letter of the word "Parameters". A blank line is left before the section title, but not after, and not between the line with the word "Parameters" and the one with the hyphens.

After the title, each parameter in the signature must be documented, including `*args` and `**kwargs`, but not `self`.

The parameters are defined by their name, followed by a space, a colon, another space, and the type (or types). Note that the space between the name and the colon is important. Types are not defined for `*args` and `**kwargs`, but must be defined for all other parameters. After the parameter definition, it is required to have a line with the parameter description, which is indented, and can have multiple lines. The description must start with a capital letter, and finish with a dot.

For keyword arguments with a default value, the default will be listed after a comma at the end of the type. The exact form of the type in this case will be "int, default 0". In some cases it may be useful to explain what the default argument means, which can be added after a comma "int, default -1, meaning all cpus".

In cases where the default value is `None`, meaning that the value will not be used. Instead of `"str, default None"`, it is preferred to write `"str, optional"`. When `None` is a value being used, we will keep the form "str, default None". For example, in `df.to_csv(compression=None)`, `None` is not a value being used, but means that compression is optional, and no compression is being used if not provided. In this case we will use `"str, optional"`. Only in cases like `func(value=None)` and `None` is being used in the same way as `0` or `foo` would be used, then we will specify "str, int or None, default None".

Good:

```
class Series:
    def plot(self, kind, color='blue', **kwargs):
        """
        Generate a plot.
```

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```
        Render the data in the Series as a matplotlib plot of the
        specified kind.

        Parameters
        ----------
        kind : str
            Kind of matplotlib plot.
        color : str, default 'blue'
            Color name or rgb code.
        **kwargs
            These parameters will be passed to the matplotlib plotting
            function.
        """
        pass
```

Bad:

```
class Series:
    def plot(self, kind, **kwargs):
        """
        Generate a plot.

        Render the data in the Series as a matplotlib plot of the
        specified kind.

        Note the blank line between the parameters title and the first
        parameter. Also, note that after the name of the parameter ``kind``
        and before the colon, a space is missing.

        Also, note that the parameter descriptions do not start with a
        capital letter, and do not finish with a dot.

        Finally, the ``**kwargs`` parameter is missing.

        Parameters
        ----------

        kind: str
            kind of matplotlib plot
        """
        pass
```

Parameter types

When specifying the parameter types, Python built-in data types can be used directly (the Python type is preferred to the more verbose string, integer, boolean, etc):

- int
- float
- str
- bool

For complex types, define the subtypes. For `dict` and `tuple`, as more than one type is present, we use the brackets to help read the type (curly brackets for `dict` and normal brackets for `tuple`):

- list of int
- dict of {str : int}
- tuple of (str, int, int)
- tuple of (str,)
- set of str

In case where there are just a set of values allowed, list them in curly brackets and separated by commas (followed by a space). If the values are ordinal and they have an order, list them in this order. Otherwise, list the default value first, if there is one:

- {0, 10, 25}
- {'simple', 'advanced'}
- {'low', 'medium', 'high'}
- {'cat', 'dog', 'bird'}

If the type is defined in a Python module, the module must be specified:

- datetime.date
- datetime.datetime
- decimal.Decimal

If the type is in a package, the module must be also specified:

- numpy.ndarray
- scipy.sparse.coo_matrix

If the type is a pandas type, also specify pandas except for Series and DataFrame:

- Series
- DataFrame
- pandas.Index
- pandas.Categorical
- pandas.arrays.SparseArray

If the exact type is not relevant, but must be compatible with a NumPy array, array-like can be specified. If Any type that can be iterated is accepted, iterable can be used:

- array-like
- iterable

If more than one type is accepted, separate them by commas, except the last two types, that need to be separated by the word 'or':

- int or float
- float, decimal.Decimal or None
- str or list of str

If `None` is one of the accepted values, it always needs to be the last in the list.

For axis, the convention is to use something like:

- axis : {0 or 'index', 1 or 'columns', None}, default None

Section 4: returns or yields

If the method returns a value, it will be documented in this section. Also if the method yields its output.

The title of the section will be defined in the same way as the "Parameters". With the names "Returns" or "Yields" followed by a line with as many hyphens as the letters in the preceding word.

The documentation of the return is also similar to the parameters. But in this case, no name will be provided, unless the method returns or yields more than one value (a tuple of values).

The types for "Returns" and "Yields" are the same as the ones for the "Parameters". Also, the description must finish with a dot.

For example, with a single value:

```
def sample():
    """
    Generate and return a random number.

    The value is sampled from a continuous uniform distribution between
    0 and 1.

    Returns
    -------
    float
        Random number generated.
    """
    return np.random.random()
```

With more than one value:

```
import string

def random_letters():
    """
    Generate and return a sequence of random letters.

    The length of the returned string is also random, and is also
    returned.

    Returns
    -------
    length : int
        Length of the returned string.
    letters : str
        String of random letters.
    """
    length = np.random.randint(1, 10)
    letters = ''.join(np.random.choice(string.ascii_lowercase)
                      for i in range(length))
    return length, letters
```

If the method yields its value:

```
def sample_values():
    """
```

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```
    Generate an infinite sequence of random numbers.

    The values are sampled from a continuous uniform distribution between
    0 and 1.

    Yields
    ------
    float
        Random number generated.
    """
    while True:
        yield np.random.random()
```

Section 5: see also

This section is used to let users know about pandas functionality related to the one being documented. In rare cases, if no related methods or functions can be found at all, this section can be skipped.

An obvious example would be the `head()` and `tail()` methods. As `tail()` does the equivalent as `head()` but at the end of the `Series` or `DataFrame` instead of at the beginning, it is good to let the users know about it.

To give an intuition on what can be considered related, here there are some examples:

- `loc` and `iloc`, as they do the same, but in one case providing indices and in the other positions
- `max` and `min`, as they do the opposite
- `iterrows`, `itertuples` and `items`, as it is easy that a user looking for the method to iterate over columns ends up in the method to iterate over rows, and vice-versa
- `fillna` and `dropna`, as both methods are used to handle missing values
- `read_csv` and `to_csv`, as they are complementary
- `merge` and `join`, as one is a generalization of the other
- `astype` and `pandas.to_datetime`, as users may be reading the documentation of `astype` to know how to cast as a date, and the way to do it is with `pandas.to_datetime`
- `where` is related to `numpy.where`, as its functionality is based on it

When deciding what is related, you should mainly use your common sense and think about what can be useful for the users reading the documentation, especially the less experienced ones.

When relating to other libraries (mainly `numpy`), use the name of the module first (not an alias like `np`). If the function is in a module which is not the main one, like `scipy.sparse`, list the full module (e.g. `scipy.sparse.coo_matrix`).

This section has a header, "See Also" (note the capital S and A), followed by the line with hyphens and preceded by a blank line.

After the header, we will add a line for each related method or function, followed by a space, a colon, another space, and a short description that illustrates what this method or function does, why is it relevant in this context, and what the key differences are between the documented function and the one being referenced. The description must also end with a dot.

Note that in "Returns" and "Yields", the description is located on the line after the type. In this section, however, it is located on the same line, with a colon in between. If the description does not fit on the same line, it can continue onto other lines which must be further indented.

For example:

```
class Series:
    def head(self):
        """
        Return the first 5 elements of the Series.

        This function is mainly useful to preview the values of the
        Series without displaying the whole of it.

        Returns
        -------
        Series
            Subset of the original series with the 5 first values.

        See Also
        --------
        Series.tail : Return the last 5 elements of the Series.
        Series.iloc : Return a slice of the elements in the Series,
            which can also be used to return the first or last n.
        """
        return self.iloc[:5]
```

Section 6: notes

This is an optional section used for notes about the implementation of the algorithm, or to document technical aspects of the function behavior.

Feel free to skip it, unless you are familiar with the implementation of the algorithm, or you discover some counter-intuitive behavior while writing the examples for the function.

This section follows the same format as the extended summary section.

Section 7: examples

This is one of the most important sections of a docstring, despite being placed in the last position, as often people understand concepts better by example than through accurate explanations.

Examples in docstrings, besides illustrating the usage of the function or method, must be valid Python code, that returns the given output in a deterministic way, and that can be copied and run by users.

Examples are presented as a session in the Python terminal. >>> is used to present code. ... is used for code continuing from the previous line. Output is presented immediately after the last line of code generating the output (no blank lines in between). Comments describing the examples can be added with blank lines before and after them.

The way to present examples is as follows:

1. Import required libraries (except `numpy` and `pandas`)
2. Create the data required for the example
3. Show a very basic example that gives an idea of the most common use case
4. Add examples with explanations that illustrate how the parameters can be used for extended functionality

A simple example could be:

```
class Series:

    def head(self, n=5):
        """
        Return the first elements of the Series.

        This function is mainly useful to preview the values of the
        Series without displaying all of it.

        Parameters
        ----------
        n : int
            Number of values to return.

        Return
        ------
        pandas.Series
            Subset of the original series with the n first values.

        See Also
        --------
        tail : Return the last n elements of the Series.

        Examples
        --------
        >>> s = pd.Series(['Ant', 'Bear', 'Cow', 'Dog', 'Falcon',
        ...                'Lion', 'Monkey', 'Rabbit', 'Zebra'])
        >>> s.head()
        0   Ant
        1   Bear
        2   Cow
        3   Dog
        4   Falcon
        dtype: object

        With the ``n`` parameter, we can change the number of returned rows:

        >>> s.head(n=3)
        0   Ant
        1   Bear
        2   Cow
        dtype: object
        """
        return self.iloc[:n]
```

The examples should be as concise as possible. In cases where the complexity of the function requires long examples, is recommended to use blocks with headers in bold. Use double star `**` to make a text bold, like in `**this example**`.

Conventions for the examples

Code in examples is assumed to always start with these two lines which are not shown:

```
import numpy as np
import pandas as pd
```

Any other module used in the examples must be explicitly imported, one per line (as recommended in **PEP 8#imports**) and avoiding aliases. Avoid excessive imports, but if needed, imports from the standard library go first, followed by third-party libraries (like matplotlib).

When illustrating examples with a single `Series` use the name `s`, and if illustrating with a single `DataFrame` use the name `df`. For indices, `idx` is the preferred name. If a set of homogeneous `Series` or `DataFrame` is used, name them `s1`, `s2`, `s3...` or `df1`, `df2`, `df3...` If the data is not homogeneous, and more than one structure is needed, name them with something meaningful, for example `df_main` and `df_to_join`.

Data used in the example should be as compact as possible. The number of rows is recommended to be around 4, but make it a number that makes sense for the specific example. For example in the `head` method, it requires to be higher than 5, to show the example with the default values. If doing the `mean`, we could use something like `[1, 2, 3]`, so it is easy to see that the value returned is the mean.

For more complex examples (grouping for example), avoid using data without interpretation, like a matrix of random numbers with columns A, B, C, D... And instead use a meaningful example, which makes it easier to understand the concept. Unless required by the example, use names of animals, to keep examples consistent. And numerical properties of them.

When calling the method, keywords arguments `head(n=3)` are preferred to positional arguments `head(3)`.

Good:

```
class Series:

    def mean(self):
        """
        Compute the mean of the input.

        Examples
        --------
        >>> s = pd.Series([1, 2, 3])
        >>> s.mean()
        2
        """
        pass


    def fillna(self, value):
        """
        Replace missing values by ``value``.

        Examples
        --------
        >>> s = pd.Series([1, np.nan, 3])
        >>> s.fillna(0)
        [1, 0, 3]
        """
        pass

    def groupby_mean(self):
```

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```
        """
        Group by index and return mean.

        Examples
        --------
        >>> s = pd.Series([380., 370., 24., 26],
        ...               name='max_speed',
        ...               index=['falcon', 'falcon', 'parrot', 'parrot'])
        >>> s.groupby_mean()
        index
        falcon    375.0
        parrot     25.0
        Name: max_speed, dtype: float64
        """
        pass

    def contains(self, pattern, case_sensitive=True, na=numpy.nan):
        """
        Return whether each value contains ``pattern``.

        In this case, we are illustrating how to use sections, even
        if the example is simple enough and does not require them.

        Examples
        --------
        >>> s = pd.Series('Antelope', 'Lion', 'Zebra', np.nan)
        >>> s.contains(pattern='a')
        0    False
        1    False
        2     True
        3      NaN
        dtype: bool

        **Case sensitivity**

        With ``case_sensitive`` set to ``False`` we can match ``a`` with both
        ``a`` and ``A``:

        >>> s.contains(pattern='a', case_sensitive=False)
        0     True
        1    False
        2     True
        3      NaN
        dtype: bool

        **Missing values**

        We can fill missing values in the output using the ``na`` parameter:

        >>> s.contains(pattern='a', na=False)
        0    False
        1    False
        2     True
        3    False
        dtype: bool
        """
        pass
```

Bad:

```
def method(foo=None, bar=None):
    """
    A sample DataFrame method.

    Do not import NumPy and pandas.

    Try to use meaningful data, when it makes the example easier
    to understand.

    Try to avoid positional arguments like in ``df.method(1)``. They
    can be all right if previously defined with a meaningful name,
    like in ``present_value(interest_rate)``, but avoid them otherwise.

    When presenting the behavior with different parameters, do not place
    all the calls one next to the other. Instead, add a short sentence
    explaining what the example shows.

    Examples
    --------
    >>> import numpy as np
    >>> import pandas as pd
    >>> df = pd.DataFrame(np.random.randn(3, 3),
    ...                   columns=('a', 'b', 'c'))
    >>> df.method(1)
    21
    >>> df.method(bar=14)
    123
    """
    pass
```

Tips for getting your examples pass the doctests

Getting the examples pass the doctests in the validation script can sometimes be tricky. Here are some attention points:

- Import all needed libraries (except for pandas and NumPy, those are already imported as `import pandas as pd` and `import numpy as np`) and define all variables you use in the example.
- Try to avoid using random data. However random data might be OK in some cases, like if the function you are documenting deals with probability distributions, or if the amount of data needed to make the function result meaningful is too much, such that creating it manually is very cumbersome. In those cases, always use a fixed random seed to make the generated examples predictable. Example:

```
>>> np.random.seed(42)
>>> df = pd.DataFrame({'normal': np.random.normal(100, 5, 20)})
```

- If you have a code snippet that wraps multiple lines, you need to use '...' on the continued lines:

```
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], index=['a', 'b', 'c'],
...                   columns=['A', 'B'])
```

- If you want to show a case where an exception is raised, you can do:

```
>>> pd.to_datetime(["712-01-01"])
Traceback (most recent call last):
OutOfBoundsDatetime: Out of bounds nanosecond timestamp: 712-01-01 00:00:00
```

It is essential to include the "Traceback (most recent call last):", but for the actual error only the error name is sufficient.

– If there is a small part of the result that can vary (e.g. a hash in an object representation), you can use `...` to represent this part.

If you want to show that `s.plot()` returns a matplotlib AxesSubplot object, this will fail the doctest

```
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at 0x7efd0c0b0690>
```

However, you can do (notice the comment that needs to be added)

```
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at ...>
```

Plots in examples

There are some methods in pandas returning plots. To render the plots generated by the examples in the documentation, the `.. plot::` directive exists.

To use it, place the next code after the "Examples" header as shown below. The plot will be generated automatically when building the documentation.

```
class Series:
    def plot(self):
        """
        Generate a plot with the ``Series`` data.

        Examples
        --------

        .. plot::
            :context: close-figs

            >>> s = pd.Series([1, 2, 3])
            >>> s.plot()
        """
        pass
```

Sharing docstrings

pandas has a system for sharing docstrings, with slight variations, between classes. This helps us keep docstrings consistent, while keeping things clear for the user reading. It comes at the cost of some complexity when writing.

Each shared docstring will have a base template with variables, like `{klass}`. The variables filled in later on using the `doc` decorator. Finally, docstrings can also be appended to with the `doc` decorator.

In this example, we'll create a parent docstring normally (this is like `pandas.core.generic.NDFrame`. Then we'll have two children (like `pandas.core.series.Series` and `pandas.core.frame.DataFrame`). We'll substitute the class names in this docstring.

```
class Parent:
    @doc(klass="Parent")
    def my_function(self):
        """Apply my function to {klass}."""
        ...


class ChildA(Parent):
    @doc(Parent.my_function, klass="ChildA")
    def my_function(self):
        ...


class ChildB(Parent):
    @doc(Parent.my_function, klass="ChildB")
    def my_function(self):
        ...
```

The resulting docstrings are

```
>>> print(Parent.my_function.__doc__)
Apply my function to Parent.
>>> print(ChildA.my_function.__doc__)
Apply my function to ChildA.
>>> print(ChildB.my_function.__doc__)
Apply my function to ChildB.
```

Notice:

1. We "append" the parent docstring to the children docstrings, which are initially empty.

Our files will often contain a module-level `_shared_doc_kwargs` with some common substitution values (things like `klass`, `axes`, etc).

You can substitute and append in one shot with something like

```
@doc(template, **_shared_doc_kwargs)
def my_function(self):
    ...
```

where `template` may come from a module-level `_shared_docs` dictionary mapping function names to docstrings. Wherever possible, we prefer using `doc`, since the docstring-writing processes is slightly closer to normal.

See `pandas.core.generic.NDFrame.fillna` for an example template, and `pandas.core.series.Series.fillna` and `pandas.core.generic.frame.fillna` for the filled versions.

- The tutorials make heavy use of the IPython directive sphinx extension. This directive lets you put code in the documentation which will be run during the doc build. For example:

```
.. ipython:: python

    x = 2
    x**3
```

will be rendered as:

```
In [1]: x = 2
```

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```
In [2]: x**3
Out[2]: 8
```

Almost all code examples in the docs are run (and the output saved) during the doc build. This approach means that code examples will always be up to date, but it does make the doc building a bit more complex.

- Our API documentation files in `doc/source/reference` house the auto-generated documentation from the docstrings. For classes, there are a few subtleties around controlling which methods and attributes have pages auto-generated.

  We have two autosummary templates for classes.

  1. `_templates/autosummary/class.rst`. Use this when you want to automatically generate a page for every public method and attribute on the class. The `Attributes` and `Methods` sections will be automatically added to the class' rendered documentation by numpydoc. See `DataFrame` for an example.
  2. `_templates/autosummary/class_without_autosummary`. Use this when you want to pick a subset of methods / attributes to auto-generate pages for. When using this template, you should include an `Attributes` and `Methods` section in the class docstring. See `CategoricalIndex` for an example.

  Every method should be included in a `toctree` in one of the documentation files in `doc/source/reference`, else Sphinx will emit a warning.

Note: The `.rst` files are used to automatically generate Markdown and HTML versions of the docs. For this reason, please do not edit `CONTRIBUTING.md` directly, but instead make any changes to `doc/source/development/contributing.rst`. Then, to generate `CONTRIBUTING.md`, use pandoc with the following command:

```
pandoc doc/source/development/contributing.rst -t markdown_github > CONTRIBUTING.md
```

The utility script `scripts/validate_docstrings.py` can be used to get a csv summary of the API documentation. And also validate common errors in the docstring of a specific class, function or method. The summary also compares the list of methods documented in the files in `doc/source/reference` (which is used to generate the API Reference page) and the actual public methods. This will identify methods documented in `doc/source/reference` that are not actually class methods, and existing methods that are not documented in `doc/source/reference`.

Updating a pandas docstring

When improving a single function or method's docstring, it is not necessarily needed to build the full documentation (see next section). However, there is a script that checks a docstring (for example for the `DataFrame.mean` method):

```
python scripts/validate_docstrings.py pandas.DataFrame.mean
```

This script will indicate some formatting errors if present, and will also run and test the examples included in the docstring. Check the *pandas docstring guide* for a detailed guide on how to format the docstring.

The examples in the docstring ('doctests') must be valid Python code, that in a deterministic way returns the presented output, and that can be copied and run by users. This can be checked with the script above, and is also tested on Travis. A failing doctest will be a blocker for merging a PR. Check the *examples* section in the docstring guide for some tips and tricks to get the doctests passing.

When doing a PR with a docstring update, it is good to post the output of the validation script in a comment on github.

How to build the pandas documentation

Requirements

First, you need to have a development environment to be able to build pandas (see the docs on *creating a development environment above*).

Building the documentation

So how do you build the docs? Navigate to your local `doc/` directory in the console and run:

```
python make.py html
```

Then you can find the HTML output in the folder `doc/build/html/`.

The first time you build the docs, it will take quite a while because it has to run all the code examples and build all the generated docstring pages. In subsequent evocations, sphinx will try to only build the pages that have been modified.

If you want to do a full clean build, do:

```
python make.py clean
python make.py html
```

You can tell `make.py` to compile only a single section of the docs, greatly reducing the turn-around time for checking your changes.

```
# omit autosummary and API section
python make.py clean
python make.py --no-api

# compile the docs with only a single section, relative to the "source" folder.
# For example, compiling only this guide (doc/source/development/contributing.rst)
python make.py clean
python make.py --single development/contributing.rst

# compile the reference docs for a single function
python make.py clean
python make.py --single pandas.DataFrame.join
```

For comparison, a full documentation build may take 15 minutes, but a single section may take 15 seconds. Subsequent builds, which only process portions you have changed, will be faster.

You can also specify to use multiple cores to speed up the documentation build:

```
python make.py html --num-jobs 4
```

Open the following file in a web browser to see the full documentation you just built:

```
doc/build/html/index.html
```

And you'll have the satisfaction of seeing your new and improved documentation!

Building master branch documentation

When pull requests are merged into the pandas `master` branch, the main parts of the documentation are also built by Travis-CI. These docs are then hosted here, see also the *Continuous Integration* section.

4.1.5 Contributing to the code base

Code Base:

- *Code standards*
- *Pre-commit*
- *Optional dependencies*
  - *C (cpplint)*
  - *Python (PEP8 / black)*
  - *Import formatting*
  - *Backwards compatibility*
- *Type hints*
  - *Style guidelines*
  - *pandas-specific types*
  - *Validating type hints*
- *Testing with continuous integration*
- *Test-driven development/code writing*
  - *Writing tests*
  - *Transitioning to `pytest`*
  - *Using `pytest`*
  - *Using `hypothesis`*
  - *Testing warnings*
- *Running the test suite*
- *Running the performance test suite*
- *Documenting your code*

Code standards

Writing good code is not just about what you write. It is also about *how* you write it. During *Continuous Integration* testing, several tools will be run to check your code for stylistic errors. Generating any warnings will cause the test to fail. Thus, good style is a requirement for submitting code to pandas.

There is a tool in pandas to help contributors verify their changes before contributing them to the project:

```
./ci/code_checks.sh
```

The script verifies the linting of code files, it looks for common mistake patterns (like missing spaces around sphinx directives that make the documentation not being rendered properly) and it also validates the doctests. It is possible to run the checks independently by using the parameters `lint`, `patterns` and `doctests` (e.g. `./ci/code_checks.sh lint`).

In addition, because a lot of people use our library, it is important that we do not make sudden changes to the code that could have the potential to break a lot of user code as a result, that is, we need it to be as *backwards compatible* as possible to avoid mass breakages.

In addition to `./ci/code_checks.sh`, some extra checks are run by `pre-commit` - see *here* for how to run them.

Additional standards are outlined on the *pandas code style guide*.

Pre-commit

You can run many of these styling checks manually as we have described above. However, we encourage you to use pre-commit hooks instead to automatically run `black`, `flake8`, `isort` when you make a git commit. This can be done by installing `pre-commit`:

```
pip install pre-commit
```

and then running:

```
pre-commit install
```

from the root of the pandas repository. Now all of the styling checks will be run each time you commit changes without your needing to run each one manually. In addition, using `pre-commit` will also allow you to more easily remain up-to-date with our code checks as they change.

Note that if needed, you can skip these checks with `git commit --no-verify`.

If you don't want to use `pre-commit` as part of your workflow, you can still use it to run its checks with:

```
pre-commit run --files <files you have modified>
```

without needing to have done `pre-commit install` beforehand.

Note: If you have conflicting installations of `virtualenv`, then you may get an error - see here.

Also, due to a bug in virtualenv, you may run into issues if you're using conda. To solve this, you can downgrade `virtualenv` to version `20.0.33`.

Optional dependencies

Optional dependencies (e.g. matplotlib) should be imported with the private helper `pandas.compat._optional.import_optional_dependency`. This ensures a consistent error message when the dependency is not met.

All methods using an optional dependency should include a test asserting that an `ImportError` is raised when the optional dependency is not found. This test should be skipped if the library is present.

All optional dependencies should be documented in *Optional dependencies* and the minimum required version should be set in the `pandas.compat._optional.VERSIONS` dict.

C (cpplint)

pandas uses the Google standard. Google provides an open source style checker called `cpplint`, but we use a fork of it that can be found here. Here are *some* of the more common `cpplint` issues:

- we restrict line-length to 80 characters to promote readability
- every header file must include a header guard to avoid name collisions if re-included

Continuous Integration will run the cpplint tool and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself:

```
cpplint --extensions=c,h --headers=h --filter=-readability/casting,-runtime/int,-
↪build/include_subdir modified-c-file
```

You can also run this command on an entire directory if necessary:

```
cpplint --extensions=c,h --headers=h --filter=-readability/casting,-runtime/int,-
↪build/include_subdir --recursive modified-c-directory
```

To make your commits compliant with this standard, you can install the ClangFormat tool, which can be downloaded here. To configure, in your home directory, run the following command:

```
clang-format style=google -dump-config  > .clang-format
```

Then modify the file to ensure that any indentation width parameters are at least four. Once configured, you can run the tool as follows:

```
clang-format modified-c-file
```

This will output what your file will look like if the changes are made, and to apply them, run the following command:

```
clang-format -i modified-c-file
```

To run the tool on an entire directory, you can run the following analogous commands:

```
clang-format modified-c-directory/*.c modified-c-directory/*.h
clang-format -i modified-c-directory/*.c modified-c-directory/*.h
```

Do note that this tool is best-effort, meaning that it will try to correct as many errors as possible, but it may not correct *all* of them. Thus, it is recommended that you run `cpplint` to double check and make any other style fixes manually.

Python (PEP8 / black)

pandas follows the PEP8 standard and uses Black and Flake8 to ensure a consistent code format throughout the project. We encourage you to use *pre-commit*.

Continuous Integration will run those tools and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself:

```
black pandas
git diff upstream/master -u -- "*.py" | flake8 --diff
```

to auto-format your code. Additionally, many editors have plugins that will apply `black` as you edit files.

You should use a `black` version 20.8b1 as previous versions are not compatible with the pandas codebase.

One caveat about `git diff upstream/master -u -- "*.py" | flake8 --diff`: this command will catch any stylistic errors in your changes specifically, but be beware it may not catch all of them. For example, if you delete the only usage of an imported function, it is stylistically incorrect to import an unused function. However, style-checking the diff will not catch this because the actual import is not part of the diff. Thus, for completeness, you should run this command, though it may take longer:

```
git diff upstream/master --name-only -- "*.py" | xargs -r flake8
```

Note that on OSX, the `-r` flag is not available, so you have to omit it and run this slightly modified command:

```
git diff upstream/master --name-only -- "*.py" | xargs flake8
```

Windows does not support the `xargs` command (unless installed for example via the MinGW toolchain), but one can imitate the behaviour as follows:

```
for /f %i in ('git diff upstream/master --name-only -- "*.py"') do flake8 %i
```

This will get all the files being changed by the PR (and ending with `.py`), and run `flake8` on them, one after the other.

Note that these commands can be run analogously with `black`.

Import formatting

pandas uses isort to standardise import formatting across the codebase.

A guide to import layout as per pep8 can be found here.

A summary of our current import sections (in order):

- Future
- Python Standard Library
- Third Party
- `pandas._libs`, `pandas.compat`, `pandas.util._*`, `pandas.errors` (largely not dependent on `pandas.core`)
- `pandas.core.dtypes` (largely not dependent on the rest of `pandas.core`)
- Rest of `pandas.core.*`
- Non-core `pandas.io`, `pandas.plotting`, `pandas.tseries`
- Local application/library specific imports

Imports are alphabetically sorted within these sections.

As part of *Continuous Integration* checks we run:

```
isort --check-only pandas
```

to check that imports are correctly formatted as per the `setup.cfg`.

If you see output like the below in *Continuous Integration* checks:

```
Check import format using isort
ERROR: /home/travis/build/pandas-dev/pandas/pandas/io/pytables.py Imports are␣
↪incorrectly sorted
Check import format using isort DONE
The command "ci/code_checks.sh" exited with 1
```

You should run:

```
isort pandas/io/pytables.py
```

to automatically format imports correctly. This will modify your local copy of the files.

Alternatively, you can run a command similar to what was suggested for `black` and `flake8` *right above*:

```
git diff upstream/master --name-only -- "*.py" | xargs -r isort
```

Where similar caveats apply if you are on OSX or Windows.

You can then verify the changes look ok, then git *commit* and *push*.

Backwards compatibility

Please try to maintain backward compatibility. pandas has lots of users with lots of existing code, so don't break it if at all possible. If you think breakage is required, clearly state why as part of the pull request. Also, be careful when changing method signatures and add deprecation warnings where needed. Also, add the deprecated sphinx directive to the deprecated functions or methods.

If a function with the same arguments as the one being deprecated exist, you can use the `pandas.util._decorators.deprecate`:

```
from pandas.util._decorators import deprecate

deprecate('old_func', 'new_func', '1.1.0')
```

Otherwise, you need to do it manually:

```
import warnings


def old_func():
    """Summary of the function.

    .. deprecated:: 1.1.0
       Use new_func instead.
    """
    warnings.warn('Use new_func instead.', FutureWarning, stacklevel=2)
    new_func()
```

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```
def new_func():
    pass
```

You'll also need to

1. Write a new test that asserts a warning is issued when calling with the deprecated argument
2. Update all of pandas existing tests and code to use the new argument

See *Testing warnings* for more.

Type hints

pandas strongly encourages the use of **PEP 484** style type hints. New development should contain type hints and pull requests to annotate existing code are accepted as well!

Style guidelines

Types imports should follow the `from typing import ...` convention. So rather than

```
import typing

primes: typing.List[int] = []
```

You should write

```
from typing import List, Optional, Union

primes: List[int] = []
```

`Optional` should be used where applicable, so instead of

```
maybe_primes: List[Union[int, None]] = []
```

You should write

```
maybe_primes: List[Optional[int]] = []
```

In some cases in the code base classes may define class variables that shadow builtins. This causes an issue as described in Mypy 1775. The defensive solution here is to create an unambiguous alias of the builtin and use that without your annotation. For example, if you come across a definition like

```
class SomeClass1:
    str = None
```

The appropriate way to annotate this would be as follows

```
str_type = str

class SomeClass2:
    str: str_type = None
```

In some cases you may be tempted to use `cast` from the typing module when you know better than the analyzer. This occurs particularly when using custom inference functions. For example

```
from typing import cast

from pandas.core.dtypes.common import is_number

def cannot_infer_bad(obj: Union[str, int, float]):

    if is_number(obj):
        ...
    else:  # Reasonably only str objects would reach this but...
        obj = cast(str, obj)  # Mypy complains without this!
        return obj.upper()
```

The limitation here is that while a human can reasonably understand that `is_number` would catch the `int` and `float` types mypy cannot make that same inference just yet (see mypy #5206. While the above works, the use of `cast` is **strongly discouraged**. Where applicable a refactor of the code to appease static analysis is preferable

```
def cannot_infer_good(obj: Union[str, int, float]):

    if isinstance(obj, str):
        return obj.upper()
    else:
        ...
```

With custom types and inference this is not always possible so exceptions are made, but every effort should be exhausted to avoid `cast` before going down such paths.

pandas-specific types

Commonly used types specific to pandas will appear in pandas._typing and you should use these where applicable. This module is private for now but ultimately this should be exposed to third party libraries who want to implement type checking against pandas.

For example, quite a few functions in pandas accept a `dtype` argument. This can be expressed as a string like `"object"`, a `numpy.dtype` like `np.int64` or even a pandas `ExtensionDtype` like `pd.CategoricalDtype`. Rather than burden the user with having to constantly annotate all of those options, this can simply be imported and reused from the pandas._typing module

```
from pandas._typing import Dtype

def as_type(dtype: Dtype) -> ...:
    ...
```

This module will ultimately house types for repeatedly used concepts like “path-like”, “array-like”, “numeric”, etc... and can also hold aliases for commonly appearing parameters like `axis`. Development of this module is active so be sure to refer to the source for the most up to date list of available types.

Validating type hints

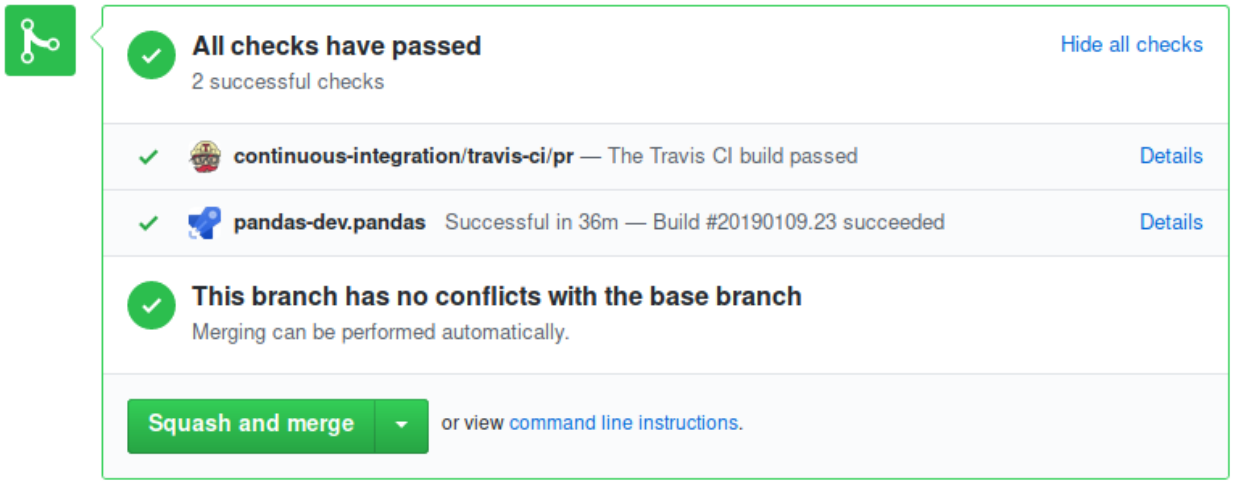
pandas uses mypy to statically analyze the code base and type hints. After making any change you can ensure your type hints are correct by running

```
mypy pandas
```

Testing with continuous integration

The pandas test suite will run automatically on Travis-CI and Azure Pipelines continuous integration services, once your pull request is submitted. However, if you wish to run the test suite on a branch prior to submitting the pull request, then the continuous integration services need to be hooked to your GitHub repository. Instructions are here for Travis-CI and Azure Pipelines.

A pull-request will be considered for merging when you have an all 'green' build. If any tests are failing, then you will get a red 'X', where you can click through to see the individual failed tests. This is an example of a green build.



Note: Each time you push to *your* fork, a *new* run of the tests will be triggered on the CI. You can enable the auto-cancel feature, which removes any non-currently-running tests for that same pull-request, for Travis-CI here.

Test-driven development/code writing

pandas is serious about testing and strongly encourages contributors to embrace test-driven development (TDD). This development process "relies on the repetition of a very short development cycle: first the developer writes an (initially failing) automated test case that defines a desired improvement or new function, then produces the minimum amount of code to pass that test." So, before actually writing any code, you should write your tests. Often the test can be taken from the original GitHub issue. However, it is always worth considering additional use cases and writing corresponding tests.

Adding tests is one of the most common requests after code is pushed to pandas. Therefore, it is worth getting in the habit of writing tests ahead of time so this is never an issue.

Like many packages, pandas uses pytest and the convenient extensions in numpy.testing.

Note: The earliest supported pytest version is 5.0.1.

Writing tests

All tests should go into the `tests` subdirectory of the specific package. This folder contains many current examples of tests, and we suggest looking to these for inspiration. If your test requires working with files or network connectivity, there is more information on the testing page of the wiki.

The `pandas._testing` module has many special `assert` functions that make it easier to make statements about whether Series or DataFrame objects are equivalent. The easiest way to verify that your code is correct is to explicitly construct the result you expect, then compare the actual result to the expected correct result:

```
def test_pivot(self):
    data = {
        'index' : ['A', 'B', 'C', 'C', 'B', 'A'],
        'columns' : ['One', 'One', 'One', 'Two', 'Two', 'Two'],
        'values' : [1., 2., 3., 3., 2., 1.]
    }

    frame = DataFrame(data)
    pivoted = frame.pivot(index='index', columns='columns', values='values')

    expected = DataFrame({
        'One' : {'A' : 1., 'B' : 2., 'C' : 3.},
        'Two' : {'A' : 1., 'B' : 2., 'C' : 3.}
    })

    assert_frame_equal(pivoted, expected)
```

Please remember to add the Github Issue Number as a comment to a new test. E.g. "# brief comment, see GH#28907"

Transitioning to `pytest`

pandas existing test structure is *mostly* class-based, meaning that you will typically find tests wrapped in a class.

```
class TestReallyCoolFeature:
    pass
```

Going forward, we are moving to a more *functional* style using the pytest framework, which offers a richer testing framework that will facilitate testing and developing. Thus, instead of writing test classes, we will write test functions like this:

```
def test_really_cool_feature():
    pass
```

Using `pytest`

Here is an example of a self-contained set of tests that illustrate multiple features that we like to use.

- functional style: tests are like `test_*` and *only* take arguments that are either fixtures or parameters
- `pytest.mark` can be used to set metadata on test functions, e.g. `skip` or `xfail`.
- using `parametrize`: allow testing of multiple cases
- to set a mark on a parameter, `pytest.param(..., marks=...)` syntax should be used
- `fixture`, code for object construction, on a per-test basis
- using bare `assert` for scalars and truth-testing
- `tm.assert_series_equal` (and its counter part `tm.assert_frame_equal`), for pandas object comparisons.
- the typical pattern of constructing an `expected` and comparing versus the `result`

We would name this file `test_cool_feature.py` and put in an appropriate place in the `pandas/tests/` structure.

```
import pytest
import numpy as np
import pandas as pd


@pytest.mark.parametrize('dtype', ['int8', 'int16', 'int32', 'int64'])
def test_dtypes(dtype):
    assert str(np.dtype(dtype)) == dtype


@pytest.mark.parametrize(
    'dtype', ['float32', pytest.param('int16', marks=pytest.mark.skip),
              pytest.param('int32', marks=pytest.mark.xfail(
                  reason='to show how it works'))])
def test_mark(dtype):
    assert str(np.dtype(dtype)) == 'float32'


@pytest.fixture
def series():
    return pd.Series([1, 2, 3])


@pytest.fixture(params=['int8', 'int16', 'int32', 'int64'])
def dtype(request):
    return request.param


def test_series(series, dtype):
    result = series.astype(dtype)
    assert result.dtype == dtype

    expected = pd.Series([1, 2, 3], dtype=dtype)
    tm.assert_series_equal(result, expected)
```

A test run of this yields

```
((pandas) bash-3.2$ pytest  test_cool_feature.py  -v
============================= test session starts ==============================
platform darwin -- Python 3.6.2, pytest-3.6.0, py-1.4.31, pluggy-0.4.0
collected 11 items

tester.py::test_dtypes[int8] PASSED
tester.py::test_dtypes[int16] PASSED
tester.py::test_dtypes[int32] PASSED
tester.py::test_dtypes[int64] PASSED
tester.py::test_mark[float32] PASSED
tester.py::test_mark[int16] SKIPPED
tester.py::test_mark[int32] xfail
tester.py::test_series[int8] PASSED
tester.py::test_series[int16] PASSED
tester.py::test_series[int32] PASSED
tester.py::test_series[int64] PASSED
```

Tests that we have `parametrized` are now accessible via the test name, for example we could run these with `-k int8` to sub-select *only* those tests which match `int8`.

```
((pandas) bash-3.2$ pytest  test_cool_feature.py  -v -k int8
============================= test session starts ==============================
platform darwin -- Python 3.6.2, pytest-3.6.0, py-1.4.31, pluggy-0.4.0
collected 11 items

test_cool_feature.py::test_dtypes[int8] PASSED
test_cool_feature.py::test_series[int8] PASSED
```

Using `hypothesis`

Hypothesis is a library for property-based testing. Instead of explicitly parametrizing a test, you can describe *all* valid inputs and let Hypothesis try to find a failing input. Even better, no matter how many random examples it tries, Hypothesis always reports a single minimal counterexample to your assertions - often an example that you would never have thought to test.

See Getting Started with Hypothesis for more of an introduction, then refer to the Hypothesis documentation for details.

```
import json
from hypothesis import given, strategies as st

any_json_value = st.deferred(lambda: st.one_of(
    st.none(), st.booleans(), st.floats(allow_nan=False), st.text(),
    st.lists(any_json_value), st.dictionaries(st.text(), any_json_value)
))


@given(value=any_json_value)
def test_json_roundtrip(value):
    result = json.loads(json.dumps(value))
    assert value == result
```

This test shows off several useful features of Hypothesis, as well as demonstrating a good use-case: checking properties that should hold over a large or complicated domain of inputs.

To keep the pandas test suite running quickly, parametrized tests are preferred if the inputs or logic are simple, with

Hypothesis tests reserved for cases with complex logic or where there are too many combinations of options or subtle interactions to test (or think of!) all of them.

Testing warnings

By default, one of pandas CI workers will fail if any unhandled warnings are emitted.

If your change involves checking that a warning is actually emitted, use `tm.assert_produces_warning(ExpectedWarning)`.

```
import pandas._testing as tm


df = pd.DataFrame()
with tm.assert_produces_warning(FutureWarning):
    df.some_operation()
```

We prefer this to the `pytest.warns` context manager because ours checks that the warning's stacklevel is set correctly. The stacklevel is what ensure the *user's* file name and line number is printed in the warning, rather than something internal to pandas. It represents the number of function calls from user code (e.g. `df.some_operation()`) to the function that actually emits the warning. Our linter will fail the build if you use `pytest.warns` in a test.

If you have a test that would emit a warning, but you aren't actually testing the warning itself (say because it's going to be removed in the future, or because we're matching a 3rd-party library's behavior), then use `pytest.mark.filterwarnings` to ignore the error.

```
@pytest.mark.filterwarnings("ignore:msg:category")
def test_thing(self):
    ...
```

If the test generates a warning of class `category` whose message starts with `msg`, the warning will be ignored and the test will pass.

If you need finer-grained control, you can use Python's usual warnings module to control whether a warning is ignored / raised at different places within a single test.

```
with warnings.catch_warnings():
    warnings.simplefilter("ignore", FutureWarning)
    # Or use warnings.filterwarnings(...)
```

Alternatively, consider breaking up the unit test.

Running the test suite

The tests can then be run directly inside your Git clone (without having to install pandas) by typing:

```
pytest pandas
```

The tests suite is exhaustive and takes around 20 minutes to run. Often it is worth running only a subset of tests first around your changes before running the entire suite.

The easiest way to do this is with:

```
pytest pandas/path/to/test.py -k regex_matching_test_name
```

Or with one of the following constructs:

```
pytest pandas/tests/[test-module].py
pytest pandas/tests/[test-module].py::[TestClass]
pytest pandas/tests/[test-module].py::[TestClass]::[test_method]
```

Using pytest-xdist, one can speed up local testing on multicore machines. To use this feature, you will need to install `pytest-xdist` via:

```
pip install pytest-xdist
```

Two scripts are provided to assist with this. These scripts distribute testing across 4 threads.

On Unix variants, one can type:

```
test_fast.sh
```

On Windows, one can type:

```
test_fast.bat
```

This can significantly reduce the time it takes to locally run tests before submitting a pull request.

For more, see the pytest documentation.

Furthermore one can run

```
pd.test()
```

with an imported pandas to run tests similarly.

Running the performance test suite

Performance matters and it is worth considering whether your code has introduced performance regressions. pandas is in the process of migrating to asv benchmarks to enable easy monitoring of the performance of critical pandas operations. These benchmarks are all found in the `pandas/asv_bench` directory, and the test results can be found here.

To use all features of asv, you will need either `conda` or `virtualenv`. For more details please check the asv installation webpage.

To install asv:

```
pip install git+https://github.com/spacetelescope/asv
```

If you need to run a benchmark, change your directory to `asv_bench/` and run:

```
asv continuous -f 1.1 upstream/master HEAD
```

You can replace `HEAD` with the name of the branch you are working on, and report benchmarks that changed by more than 10%. The command uses `conda` by default for creating the benchmark environments. If you want to use virtualenv instead, write:

```
asv continuous -f 1.1 -E virtualenv upstream/master HEAD
```

The `-E virtualenv` option should be added to all `asv` commands that run benchmarks. The default value is defined in `asv.conf.json`.

Running the full benchmark suite can be an all-day process, depending on your hardware and its resource utilization. However, usually it is sufficient to paste only a subset of the results into the pull request to show that the

committed changes do not cause unexpected performance regressions. You can run specific benchmarks using the `-b` flag, which takes a regular expression. For example, this will only run benchmarks from a `pandas/asv_bench/benchmarks/groupby.py` file:

```
asv continuous -f 1.1 upstream/master HEAD -b ^groupby
```

If you want to only run a specific group of benchmarks from a file, you can do it using `.` as a separator. For example:

```
asv continuous -f 1.1 upstream/master HEAD -b groupby.GroupByMethods
```

will only run the `GroupByMethods` benchmark defined in `groupby.py`.

You can also run the benchmark suite using the version of `pandas` already installed in your current Python environment. This can be useful if you do not have virtualenv or conda, or are using the `setup.py develop` approach discussed above; for the in-place build you need to set `PYTHONPATH`, e.g. `PYTHONPATH="$PWD/.." asv [remaining arguments]`. You can run benchmarks using an existing Python environment by:

```
asv run -e -E existing
```

or, to use a specific Python interpreter,:

```
asv run -e -E existing:python3.6
```

This will display stderr from the benchmarks, and use your local `python` that comes from your `$PATH`.

Information on how to write a benchmark and how to use asv can be found in the asv documentation.

Documenting your code

Changes should be reflected in the release notes located in `doc/source/whatsnew/vx.y.z.rst`. This file contains an ongoing change log for each release. Add an entry to this file to document your fix, enhancement or (unavoidable) breaking change. Make sure to include the GitHub issue number when adding your entry (using `:issue:`1234`` where `1234` is the issue/pull request number).

If your code is an enhancement, it is most likely necessary to add usage examples to the existing documentation. This can be done following the section regarding documentation *above*. Further, to let users know when this feature was added, the `versionadded` directive is used. The sphinx syntax for that is:

```
.. versionadded:: 1.1.0
```

This will put the text *New in version 1.1.0* wherever you put the sphinx directive. This should also be put in the docstring when adding a new function or method (example) or a new keyword argument (example).

4.1.6 Contributing your changes to pandas

Committing your code

Keep style fixes to a separate commit to make your pull request more readable.

Once you've made changes, you can see them by typing:

```
git status
```

If you have created a new file, it is not being tracked by git. Add it by typing:

```
git add path/to/file-to-be-added.py
```

Doing 'git status' again should give something like:

```
# On branch shiny-new-feature
#
#       modified:   /relative/path/to/file-you-added.py
#
```

Finally, commit your changes to your local repository with an explanatory message. pandas uses a convention for commit message prefixes and layout. Here are some common prefixes along with general guidelines for when to use them:

- ENH: Enhancement, new functionality
- BUG: Bug fix
- DOC: Additions/updates to documentation
- TST: Additions/updates to tests
- BLD: Updates to the build process/scripts
- PERF: Performance improvement
- TYP: Type annotations
- CLN: Code cleanup

The following defines how a commit message should be structured. Please reference the relevant GitHub issues in your commit message using GH1234 or #1234. Either style is fine, but the former is generally preferred:

- a subject line with `< 80` chars.
- One blank line.
- Optionally, a commit message body.

Now you can commit your changes in your local repository:

```
git commit -m
```

Pushing your changes

When you want your changes to appear publicly on your GitHub page, push your forked feature branch's commits:

```
git push origin shiny-new-feature
```

Here `origin` is the default name given to your remote repository on GitHub. You can see the remote repositories:

```
git remote -v
```

If you added the upstream repository as described above you will see something like:

```
origin  git@github.com:yourname/pandas.git (fetch)
origin  git@github.com:yourname/pandas.git (push)
upstream        git://github.com/pandas-dev/pandas.git (fetch)
upstream        git://github.com/pandas-dev/pandas.git (push)
```

Now your code is on GitHub, but it is not yet a part of the pandas project. For that to happen, a pull request needs to be submitted on GitHub.

Review your code

When you're ready to ask for a code review, file a pull request. Before you do, once again make sure that you have followed all the guidelines outlined in this document regarding code style, tests, performance tests, and documentation. You should also double check your branch changes against the branch it was based on:

1. Navigate to your repository on GitHub – https://github.com/your-user-name/pandas
2. Click on `Branches`
3. Click on the `Compare` button for your feature branch
4. Select the `base` and `compare` branches, if necessary. This will be `master` and `shiny-new-feature`, respectively.

Finally, make the pull request

If everything looks good, you are ready to make a pull request. A pull request is how code from a local repository becomes available to the GitHub community and can be looked at and eventually merged into the master version. This pull request and its associated changes will eventually be committed to the master branch and available in the next release. To submit a pull request:

1. Navigate to your repository on GitHub
2. Click on the `Pull Request` button
3. You can then click on `Commits` and `Files Changed` to make sure everything looks okay one last time
4. Write a description of your changes in the `Preview Discussion` tab
5. Click `Send Pull Request`.

This request then goes to the repository maintainers, and they will review the code.

Updating your pull request

Based on the review you get on your pull request, you will probably need to make some changes to the code. In that case, you can make them in your branch, add a new commit to that branch, push it to GitHub, and the pull request will be automatically updated. Pushing them to GitHub again is done by:

```
git push origin shiny-new-feature
```

This will automatically update your pull request with the latest code and restart the *Continuous Integration* tests.

Another reason you might need to update your pull request is to solve conflicts with changes that have been merged into the master branch since you opened your pull request.

To do this, you need to "merge upstream master" in your branch:

```
git checkout shiny-new-feature
git fetch upstream
git merge upstream/master
```

If there are no conflicts (or they could be fixed automatically), a file with a default commit message will open, and you can simply save and quit this file.

If there are merge conflicts, you need to solve those conflicts. See for example at https://help.github.com/articles/resolving-a-merge-conflict-using-the-command-line/ for an explanation on how to do this. Once the conflicts are merged and the files where the conflicts were solved are added, you can run `git commit` to save those fixes.

If you have uncommitted changes at the moment you want to update the branch with master, you will need to `stash` them prior to updating (see the stash docs). This will effectively store your changes and they can be reapplied after updating.

After the feature branch has been update locally, you can now update your pull request by pushing to the branch on GitHub:

```
git push origin shiny-new-feature
```

Delete your merged branch (optional)

Once your feature branch is accepted into upstream, you'll probably want to get rid of the branch. First, merge upstream master into your branch so git knows it is safe to delete your branch:

```
git fetch upstream
git checkout master
git merge upstream/master
```

Then you can do:

```
git branch -d shiny-new-feature
```

Make sure you use a lower-case `-d`, or else git won't warn you if your feature branch has not actually been merged.

The branch will still exist on GitHub, so to delete it there do:

```
git push origin --delete shiny-new-feature
```

4.1.7 Tips for a successful pull request

If you have made it to the *Review your code* phase, one of the core contributors may take a look. Please note however that a handful of people are responsible for reviewing all of the contributions, which can often lead to bottlenecks.

To improve the chances of your pull request being reviewed, you should:

- **Reference an open issue** for non-trivial changes to clarify the PR's purpose
- **Ensure you have appropriate tests**. These should be the first part of any PR
- **Keep your pull requests as simple as possible**. Larger PRs take longer to review
- **Ensure that CI is in a green state**. Reviewers may not even look otherwise
- **Keep** *Updating your pull request*, either by request or every few days

4.2 pandas code style guide

Table of contents:

- *Patterns*
  - *Using foo.__class__*
- *String formatting*

- *Concatenated strings*
  - *Using f-strings*
  - *White spaces*
- *Representation function (aka 'repr()')*

- *Imports (aim for absolute)*
- *Miscellaneous*
  - *Reading from a url*

pandas follows the PEP8 standard and uses Black and Flake8 to ensure a consistent code format throughout the project. We encourage you to use *pre-commit* to automatically run `black`, `flake8`, `isort`, and related code checks when you make a git commit.

4.2.1 Patterns

Using foo.__class__

pandas uses 'type(foo)' instead 'foo.__class__' as it is making the code more readable. For example:

Good:

```
foo = "bar"
type(foo)
```

Bad:

```
foo = "bar"
foo.__class__
```

4.2.2 String formatting

Concatenated strings

Using f-strings

pandas uses f-strings formatting instead of '%' and '.format()' string formatters.

The convention of using f-strings on a string that is concatenated over several lines, is to prefix only the lines containing values which need to be interpreted.

For example:

Good:

```
foo = "old_function"
bar = "new_function"

my_warning_message = (
    f"Warning, {foo} is deprecated, "
    "please use the new and way better "
    f"{bar}"
)
```

Bad:

```
foo = "old_function"
bar = "new_function"

my_warning_message = (
    f"Warning, {foo} is deprecated, "
    f"please use the new and way better "
    f"{bar}"
)
```

White spaces

Only put white space at the end of the previous line, so there is no whitespace at the beginning of the concatenated string.

For example:

Good:

```
example_string = (
    "Some long concatenated string, "
    "with good placement of the "
    "whitespaces"
)
```

Bad:

```
example_string = (
    "Some long concatenated string,"
    " with bad placement of the"
    " whitespaces"
)
```

Representation function (aka 'repr()')

pandas uses 'repr()' instead of '%r' and '!r'.

The use of 'repr()' will only happen when the value is not an obvious string.

For example:

Good:

```
value = str
f"Unknown received value, got: {repr(value)}"
```

Good:

```
value = str
f"Unknown received type, got: '{type(value).__name__}'"
```

4.2.3 Imports (aim for absolute)

In Python 3, absolute imports are recommended. Using absolute imports, doing something like `import string` will import the string module rather than `string.py` in the same directory. As much as possible, you should try to write out absolute imports that show the whole import chain from top-level pandas.

Explicit relative imports are also supported in Python 3 but it is not recommended to use them. Implicit relative imports should never be used and are removed in Python 3.

For example:

```
# preferred
import pandas.core.common as com

# not preferred
from .common import test_base

# wrong
from common import test_base
```

4.2.4 Miscellaneous

Reading from a url

Good:

```
from pandas.io.common import urlopen

with urlopen("http://www.google.com") as url:
    raw_text = url.read()
```

4.3 pandas maintenance

This guide is for pandas' maintainers. It may also be interesting to contributors looking to understand the pandas development process and what steps are necessary to become a maintainer.

The main contributing guide is available at *Contributing to pandas*.

4.3.1 Roles

pandas uses two levels of permissions: **triage** and **core** team members.

Triage members can label and close issues and pull requests.

Core team members can label and close issues and pull request, and can merge pull requests.

GitHub publishes the full list of permissions.

4.3.2 Tasks

pandas is largely a volunteer project, so these tasks shouldn't be read as "expectations" of triage and maintainers. Rather, they're general descriptions of what it means to be a maintainer.

- Triage newly filed issues (see *Issue triage*)
- Review newly opened pull requests
- Respond to updates on existing issues and pull requests
- Drive discussion and decisions on stalled issues and pull requests
- Provide experience / wisdom on API design questions to ensure consistency and maintainability
- Project organization (run / attend developer meetings, represent pandas)

https://matthewrocklin.com/blog/2019/05/18/maintainer may be interesting background reading.

4.3.3 Issue triage

Here's a typical workflow for triaging a newly opened issue.

1. **Thank the reporter for opening an issue**

   The issue tracker is many people's first interaction with the pandas project itself, beyond just using the library. As such, we want it to be a welcoming, pleasant experience.

2. **Is the necessary information provided?**

   Ideally reporters would fill out the issue template, but many don't. If crucial information (like the version of pandas they used), is missing feel free to ask for that and label the issue with "Needs info". The report should follow the guidelines in *Bug reports and enhancement requests*. You may want to link to that if they didn't follow the template.

   Make sure that the title accurately reflects the issue. Edit it yourself if it's not clear.

3. **Is this a duplicate issue?**

   We have many open issues. If a new issue is clearly a duplicate, label the new issue as "Duplicate" assign the milestone "No Action", and close the issue with a link to the original issue. Make sure to still thank the reporter, and encourage them to chime in on the original issue, and perhaps try to fix it.

   If the new issue provides relevant information, such as a better or slightly different example, add it to the original issue as a comment or an edit to the original post.

4. **Is the issue minimal and reproducible**?

   For bug reports, we ask that the reporter provide a minimal reproducible example. See https://matthewrocklin.com/blog/work/2018/02/28/minimal-bug-reports for a good explanation. If the example is not reproducible, or if it's *clearly* not minimal, feel free to ask the reporter if they can provide and example or simplify the provided one. Do acknowledge that writing minimal reproducible examples is hard work. If the reporter is struggling, you can try to write one yourself and we'll edit the original post to include it.

   If a reproducible example can't be provided, add the "Needs info" label.

   If a reproducible example is provided, but you see a simplification, edit the original post with your simpler reproducible example.

5. **Is this a clearly defined feature request?**

   Generally, pandas prefers to discuss and design new features in issues, before a pull request is made. Encourage the submitter to include a proposed API for the new feature. Having them write a full docstring is a good way to pin down specifics.

We'll need a discussion from several pandas maintainers before deciding whether the proposal is in scope for pandas.

6. **Is this a usage question?**

   We prefer that usage questions are asked on StackOverflow with the pandas tag. https://stackoverflow.com/questions/tagged/pandas

   If it's easy to answer, feel free to link to the relevant documentation section, let them know that in the future this kind of question should be on StackOverflow, and close the issue.

7. **What labels and milestones should I add?**

   Apply the relevant labels. This is a bit of an art, and comes with experience. Look at similar issues to get a feel for how things are labeled.

   If the issue is clearly defined and the fix seems relatively straightforward, label the issue as "Good first issue".

   Typically, new issues will be assigned the "Contributions welcome" milestone, unless it's know that this issue should be addressed in a specific release (say because it's a large regression).

4.3.4 Closing issues

Be delicate here: many people interpret closing an issue as us saying that the conversation is over. It's typically best to give the reporter some time to respond or self-close their issue if it's determined that the behavior is not a bug, or the feature is out of scope. Sometimes reporters just go away though, and we'll close the issue after the conversation has died.

4.3.5 Reviewing pull requests

Anybody can review a pull request: regular contributors, triagers, or core-team members. But only core-team members can merge pull requets when they're ready.

Here are some things to check when reviewing a pull request.

- Tests should be in a sensible location: in the same file as closely related tests.
- New public APIs should be included somewhere in `doc/source/reference/`.
- New / changed API should use the `versionadded` or `versionchanged` directives in the docstring.
- User-facing changes should have a whatsnew in the appropriate file.
- Regression tests should reference the original GitHub issue number like `# GH-1234`.
- The pull request should be labeled and assigned the appropriate milestone (the next patch release for regression fixes and small bug fixes, the next minor milestone otherwise)
- Changes should comply with our *Version policy*.

4.3.6 Cleaning up old issues

Every open issue in pandas has a cost. Open issues make finding duplicates harder, and can make it harder to know what needs to be done in pandas. That said, closing issues isn't a goal on its own. Our goal is to make pandas the best it can be, and that's best done by ensuring that the quality of our open issues is high.

Occasionally, bugs are fixed but the issue isn't linked to in the Pull Request. In these cases, comment that "This has been fixed, but could use a test." and label the issue as "Good First Issue" and "Needs Test".

If an older issue doesn't follow our issue template, edit the original post to include a minimal example, the actual output, and the expected output. Uniformity in issue reports is valuable.

If an older issue lacks a reproducible example, label it as "Needs Info" and ask them to provide one (or write one yourself if possible). If one isn't provide reasonably soon, close it according to the policies in *Closing issues*.

4.3.7 Cleaning up old pull requests

Occasionally, contributors are unable to finish off a pull request. If some time has passed (two weeks, say) since the last review requesting changes, gently ask if they're still interested in working on this. If another two weeks or so passes with no response, thank them for their work and close the pull request. Comment on the original issue that "There's a stalled PR at #1234 that may be helpful.", and perhaps label the issue as "Good first issue" if the PR was relatively close to being accepted.

Additionally, core-team members can push to contributors branches. This can be helpful for pushing an important PR across the line, or for fixing a small merge conflict.

4.3.8 Becoming a pandas maintainer

The full process is outlined in our governance documents. In summary, we're happy to give triage permissions to anyone who shows interest by being helpful on the issue tracker.

The current list of core-team members is at https://github.com/pandas-dev/pandas-governance/blob/master/people.md

4.3.9 Merging pull requests

Only core team members can merge pull requests. We have a few guidelines.

1. You should typically not self-merge your own pull requests. Exceptions include things like small changes to fix CI (e.g. pinning a package version).
2. You should not merge pull requests that have an active discussion, or pull requests that has any `-1` votes from a core maintainer. pandas operates by consensus.
3. For larger changes, it's good to have a +1 from at least two core team members.

In addition to the items listed in *Closing issues*, you should verify that the pull request is assigned the correct milestone.

Pull requests merged with a patch-release milestone will typically be backported by our bot. Verify that the bot noticed the merge (it will leave a comment within a minute typically). If a manual backport is needed please do that, and remove the "Needs backport" label once you've done it manually. If you forget to assign a milestone before tagging, you can request the bot to backport it with:

```
@Meeseeksdev backport <branch>
```

4.4 Internals

This section will provide a look into some of pandas internals. It's primarily intended for developers of pandas itself.

4.4.1 Indexing

In pandas there are a few objects implemented which can serve as valid containers for the axis labels:

- `Index`: the generic "ordered set" object, an ndarray of object dtype assuming nothing about its contents. The labels must be hashable (and likely immutable) and unique. Populates a dict of label to location in Cython to do `O(1)` lookups.
- `Int64Index`: a version of `Index` highly optimized for 64-bit integer data, such as time stamps
- `Float64Index`: a version of `Index` highly optimized for 64-bit float data
- `MultiIndex`: the standard hierarchical index object
- `DatetimeIndex`: An Index object with `Timestamp` boxed elements (impl are the int64 values)
- `TimedeltaIndex`: An Index object with `Timedelta` boxed elements (impl are the in64 values)
- `PeriodIndex`: An Index object with Period elements

There are functions that make the creation of a regular index easy:

- `date_range`: fixed frequency date range generated from a time rule or DateOffset. An ndarray of Python datetime objects
- `period_range`: fixed frequency date range generated from a time rule or DateOffset. An ndarray of `Period` objects, representing timespans

The motivation for having an `Index` class in the first place was to enable different implementations of indexing. This means that it's possible for you, the user, to implement a custom `Index` subclass that may be better suited to a particular application than the ones provided in pandas.

From an internal implementation point of view, the relevant methods that an `Index` must define are one or more of the following (depending on how incompatible the new object internals are with the `Index` functions):

- `get_loc`: returns an "indexer" (an integer, or in some cases a slice object) for a label
- `slice_locs`: returns the "range" to slice between two labels
- `get_indexer`: Computes the indexing vector for reindexing / data alignment purposes. See the source / docstrings for more on this
- `get_indexer_non_unique`: Computes the indexing vector for reindexing / data alignment purposes when the index is non-unique. See the source / docstrings for more on this
- `reindex`: Does any pre-conversion of the input index then calls `get_indexer`
- `union`, `intersection`: computes the union or intersection of two Index objects
- `insert`: Inserts a new label into an Index, yielding a new object
- `delete`: Delete a label, yielding a new object
- `drop`: Deletes a set of labels
- `take`: Analogous to ndarray.take

MultiIndex

Internally, the `MultiIndex` consists of a few things: the **levels**, the integer **codes** (until version 0.24 named *labels*), and the level **names**:

```
In [1]: index = pd.MultiIndex.from_product(
   ...:     [range(3), ["one", "two"]], names=["first", "second"]
   ...: )
   ...:

In [2]: index
Out[2]:
MultiIndex([(0, 'one'),
            (0, 'two'),
            (1, 'one'),
            (1, 'two'),
            (2, 'one'),
            (2, 'two')],
           names=['first', 'second'])

In [3]: index.levels
Out[3]: FrozenList([[0, 1, 2], ['one', 'two']])

In [4]: index.codes
Out[4]: FrozenList([[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])

In [5]: index.names
Out[5]: FrozenList(['first', 'second'])
```

You can probably guess that the codes determine which unique element is identified with that location at each layer of the index. It's important to note that sortedness is determined **solely** from the integer codes and does not check (or care) whether the levels themselves are sorted. Fortunately, the constructors `from_tuples` and `from_arrays` ensure that this is true, but if you compute the levels and codes yourself, please be careful.

Values

pandas extends NumPy's type system with custom types, like `Categorical` or datetimes with a timezone, so we have multiple notions of "values". For 1-D containers (`Index` classes and `Series`) we have the following convention:

- `cls._values` refers is the "best possible" array. This could be an `ndarray` or `ExtensionArray`.

So, for example, `Series[category]._values` is a `Categorical`.

4.4.2 Subclassing pandas data structures

This section has been moved to *Subclassing pandas data structures*.

4.5 Test organization

Ideally, there should be one, and only one, obvious place for a test to reside. Until we reach that ideal, these are some rules of thumb for where a test should be located.

1. Does your test depend only on code in `pd._libs.tslibs`? This test likely belongs in one of:

   - tests.tslibs

     Note: No file in `tests.tslibs` should import from any pandas modules outside of `pd._libs.tslibs`

   - tests.scalar
   - tests.tseries.offsets

2. Does your test depend only on code in pd._libs? This test likely belongs in one of:

   - tests.libs
   - tests.groupby.test_libgroupby

3. Is your test for an arithmetic or comparison method? This test likely belongs in one of:

   - tests.arithmetic

     Note: These are intended for tests that can be shared to test the behavior of DataFrame/Series/Index/ExtensionArray using the `box_with_array` fixture.

   - tests.frame.test_arithmetic
   - tests.series.test_arithmetic

4. Is your test for a reduction method (min, max, sum, prod, ...)? This test likely belongs in one of:

   - tests.reductions

     Note: These are intended for tests that can be shared to test the behavior of DataFrame/Series/Index/ExtensionArray.

   - tests.frame.test_reductions
   - tests.series.test_reductions
   - tests.test_nanops

5. Is your test for an indexing method? This is the most difficult case for deciding where a test belongs, because there are many of these tests, and many of them test more than one method (e.g. both `Series.__getitem__` and `Series.loc.__getitem__`)

   A) Is the test specifically testing an Index method (e.g. `Index.get_loc`, `Index.get_indexer`)? This test likely belongs in one of:

      - tests.indexes.test_indexing
      - tests.indexes.fooindex.test_indexing

      Within that files there should be a method-specific test class e.g. `TestGetLoc`.

      In most cases, neither `Series` nor `DataFrame` objects should be needed in these tests.

B) Is the test for a Series or DataFrame indexing method *other* than `__getitem__` or `__setitem__`, e.g. `xs`, `where`, `take`, `mask`, `lookup`, or `insert`? This test likely belongs in one of:

- tests.frame.indexing.test_methodname
- tests.series.indexing.test_methodname

C) Is the test for any of `loc`, `iloc`, `at`, or `iat`? This test likely belongs in one of:

- tests.indexing.test_loc
- tests.indexing.test_iloc
- tests.indexing.test_at
- tests.indexing.test_iat

Within the appropriate file, test classes correspond to either types of indexers (e.g. `TestLocBooleanMask`) or major use cases (e.g. `TestLocSetitemWithExpansion`).

See the note in section D) about tests that test multiple indexing methods.

D) Is the test for `Series.__getitem__`, `Series.__setitem__`, `DataFrame.__getitem__`, or `DataFrame.__setitem__`? This test likely belongs in one of:

- tests.series.test_getitem
- tests.series.test_setitem
- tests.frame.test_getitem
- tests.frame.test_setitem

If many cases such a test may test multiple similar methods, e.g.

```
import pandas as pd
import pandas._testing as tm

def test_getitem_listlike_of_ints():
    ser = pd.Series(range(5))

    result = ser[[3, 4]]
    expected = pd.Series([2, 3])
    tm.assert_series_equal(result, expected)

    result = ser.loc[[3, 4]]
    tm.assert_series_equal(result, expected)
```

In cases like this, the test location should be based on the *underlying* method being tested. Or in the case of a test for a bugfix, the location of the actual bug. So in this example, we know that `Series.__getitem__` calls `Series.loc.__getitem__`, so this is *really* a test for `loc.__getitem__`. So this test belongs in `tests.indexing.test_loc`.

6. Is your test for a DataFrame or Series method?

A) Is the method a plotting method? This test likely belongs in one of:

- tests.plotting

B) Is the method an IO method? This test likely belongs in one of:

- tests.io

C) Otherwise This test likely belongs in one of:

- tests.series.methods.test_mymethod

- tests.frame.methods.test_mymethod

Note: If a test can be shared between DataFrame/Series using the `frame_or_series` fixture, by convention it goes in the `tests.frame` file.

- tests.generic.methods.test_mymethod

Note: The generic/methods/ directory is only for methods with tests that are fully parametrized over Series/DataFrame

7. Is your test for an Index method, not depending on Series/DataFrame? This test likely belongs in one of:
   - tests.indexes

8) Is your test for one of the pandas-provided ExtensionArrays (`Categorical`, `DatetimeArray`, `TimedeltaArray`, `PeriodArray`, `IntervalArray`, `PandasArray`, `FloatArray`, `BoolArray`, `StringArray`)? This test likely belongs in one of:
   - tests.arrays

9) Is your test for *all* ExtensionArray subclasses (the "EA Interface")? This test likely belongs in one of:
   - tests.extension

4.6 Debugging C extensions

Pandas uses select C extensions for high performance IO operations. In case you need to debug segfaults or general issues with those extensions, the following steps may be helpful.

First, be sure to compile the extensions with the appropriate flags to generate debug symbols and remove optimizations. This can be achieved as follows:

```
python setup.py build_ext --inplace -j4 --with-debugging-symbols
```

4.6.1 Using a debugger

Assuming you are on a Unix-like operating system, you can use either lldb or gdb to debug. The choice between either is largely dependent on your compilation toolchain - typically you would use lldb if using clang and gdb if using gcc. For macOS users, please note that `gcc` is on modern systems an alias for `clang`, so if using Xcode you usually opt for lldb. Regardless of which debugger you choose, please refer to your operating systems instructions on how to install.

After installing a debugger you can create a script that hits the extension module you are looking to debug. For demonstration purposes, let's assume you have a script called `debug_testing.py` with the following contents:

```
import pandas as pd

pd.DataFrame([[1, 2]]).to_json()
```

Place the `debug_testing.py` script in the project root and launch a Python process under your debugger. If using lldb:

```
lldb python
```

If using gdb:

```
gdb python
```

Before executing our script, let's set a breakpoint in our JSON serializer in its entry function called `objToJSON`. The lldb syntax would look as follows:

```
breakpoint set --name objToJSON
```

Similarly for gdb:

```
break objToJSON
```

Note: You may get a warning that this breakpoint cannot be resolved in lldb. gdb may give a similar warning and prompt you to make the breakpoint on a future library load, which you should say yes to. This should only happen on the very first invocation as the module you wish to debug has not yet been loaded into memory.

Now go ahead and execute your script:

```
run <the_script>.py
```

Code execution will halt at the breakpoint defined or at the occurance of any segfault. LLDB's GDB to LLDB command map provides a listing of debugger command that you can execute using either debugger.

Another option to execute the entire test suite under lldb would be to run the following:

```
lldb -- python -m pytest
```

Or for gdb

```
gdb --args python -m pytest
```

Once the process launches, simply type `run` and the test suite will begin, stopping at any segmentation fault that may occur.

4.6.2 Checking memory leaks with valgrind

You can use Valgrind to check for and log memory leaks in extensions. For instance, to check for a memory leak in a test from the suite you can run:

```
PYTHONMALLOC=malloc valgrind --leak-check=yes --track-origins=yes --log-file=valgrind-
↪log.txt python -m pytest <path_to_a_test>
```

Note that code execution under valgrind will take much longer than usual. While you can run valgrind against extensions compiled with any optimization level, it is suggested to have optimizations turned off from compiled extensions to reduce the amount of false positives. The `--with-debugging-symbols` flag passed during package setup will do this for you automatically.

Note: For best results, you should run use a Python installation configured with Valgrind support (–with-valgrind)

4.7 Extending pandas

While pandas provides a rich set of methods, containers, and data types, your needs may not be fully satisfied. pandas offers a few options for extending pandas.

4.7.1 Registering custom accessors

Libraries can use the decorators *pandas.api.extensions.register_dataframe_accessor()*, *pandas.api.extensions.register_series_accessor()*, and *pandas.api.extensions.register_index_accessor()*, to add additional "namespaces" to pandas objects. All of these follow a similar convention: you decorate a class, providing the name of attribute to add. The class's `__init__` method gets the object being decorated. For example:

```
@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._validate(pandas_obj)
        self._obj = pandas_obj

    @staticmethod
    def _validate(obj):
        # verify there is a column latitude and a column longitude
        if "latitude" not in obj.columns or "longitude" not in obj.columns:
            raise AttributeError("Must have 'latitude' and 'longitude'.")

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Now users can access your methods using the `geo` namespace:

```
>>> ds = pd.Dataframe(
...     {"longitude": np.linspace(0, 10), "latitude": np.linspace(0, 20)}
... )
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

This can be a convenient way to extend pandas objects without subclassing them. If you write a custom accessor, make a pull request adding it to our ecosystem page.

We highly recommend validating the data in your accessor's `__init__`. In our `GeoAccessor`, we validate that the data contains the expected columns, raising an `AttributeError` when the validation fails. For a `Series` accessor, you should validate the `dtype` if the accessor applies only to certain dtypes.

4.7.2 Extension types

Warning: The *pandas.api.extensions.ExtensionDtype* and *pandas.api.extensions.ExtensionArray* APIs are new and experimental. They may change between versions without warning.

pandas defines an interface for implementing data types and arrays that *extend* NumPy's type system. pandas itself uses the extension system for some types that aren't built into NumPy (categorical, period, interval, datetime with timezone).

Libraries can define a custom array and data type. When pandas encounters these objects, they will be handled properly (i.e. not converted to an ndarray of objects). Many methods like *pandas.isna()* will dispatch to the extension type's implementation.

If you're building a library that implements the interface, please publicize it on ecosystem.extensions.

The interface consists of two classes.

ExtensionDtype

A *pandas.api.extensions.ExtensionDtype* is similar to a `numpy.dtype` object. It describes the data type. Implementors are responsible for a few unique items like the name.

One particularly important item is the `type` property. This should be the class that is the scalar type for your data. For example, if you were writing an extension array for IP Address data, this might be `ipaddress.IPv4Address`.

See the extension dtype source for interface definition.

New in version 0.24.0.

`pandas.api.extension.ExtensionDtype` can be registered to pandas to allow creation via a string dtype name. This allows one to instantiate `Series` and `.astype()` with a registered string name, for example `'category'` is a registered string accessor for the `CategoricalDtype`.

See the extension dtype dtypes for more on how to register dtypes.

ExtensionArray

This class provides all the array-like functionality. ExtensionArrays are limited to 1 dimension. An ExtensionArray is linked to an ExtensionDtype via the `dtype` attribute.

pandas makes no restrictions on how an extension array is created via its `__new__` or `__init__`, and puts no restrictions on how you store your data. We do require that your array be convertible to a NumPy array, even if this is relatively expensive (as it is for `Categorical`).

They may be backed by none, one, or many NumPy arrays. For example, `pandas.Categorical` is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 addresses may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists.

See the extension array source for the interface definition. The docstrings and comments contain guidance for properly implementing the interface.

`ExtensionArray` operator support

New in version 0.24.0.

By default, there are no operators defined for the class *`ExtensionArray`*. There are two approaches for providing operator support for your ExtensionArray:

1. Define each of the operators on your `ExtensionArray` subclass.
2. Use an operator implementation from pandas that depends on operators that are already defined on the underlying elements (scalars) of the ExtensionArray.

Note: Regardless of the approach, you may want to set `__array_priority__` if you want your implementation to be called when involved in binary operations with NumPy arrays.

For the first approach, you define selected operators, e.g., `__add__`, `__le__`, etc. that you want your `ExtensionArray` subclass to support.

The second approach assumes that the underlying elements (i.e., scalar type) of the `ExtensionArray` have the individual operators already defined. In other words, if your `ExtensionArray` named `MyExtensionArray` is implemented so that each element is an instance of the class `MyExtensionElement`, then if the operators are defined for `MyExtensionElement`, the second approach will automatically define the operators for `MyExtensionArray`.

A mixin class, `ExtensionScalarOpsMixin` supports this second approach. If developing an `ExtensionArray` subclass, for example `MyExtensionArray`, can simply include `ExtensionScalarOpsMixin` as a parent class of `MyExtensionArray`, and then call the methods `_add_arithmetic_ops()` and/or `_add_comparison_ops()` to hook the operators into your `MyExtensionArray` class, as follows:

```
from pandas.api.extensions import ExtensionArray, ExtensionScalarOpsMixin


class MyExtensionArray(ExtensionArray, ExtensionScalarOpsMixin):
    pass


MyExtensionArray._add_arithmetic_ops()
MyExtensionArray._add_comparison_ops()
```

Note: Since `pandas` automatically calls the underlying operator on each element one-by-one, this might not be as performant as implementing your own version of the associated operators directly on the `ExtensionArray`.

For arithmetic operations, this implementation will try to reconstruct a new `ExtensionArray` with the result of the element-wise operation. Whether or not that succeeds depends on whether the operation returns a result that's valid for the `ExtensionArray`. If an `ExtensionArray` cannot be reconstructed, an ndarray containing the scalars returned instead.

For ease of implementation and consistency with operations between pandas and NumPy ndarrays, we recommend *not* handling Series and Indexes in your binary ops. Instead, you should detect these cases and return `NotImplemented`. When pandas encounters an operation like `op(Series, ExtensionArray)`, pandas will

1. unbox the array from the `Series` (`Series.array`)
2. call `result = op(values, ExtensionArray)`
3. re-box the result in a `Series`

NumPy universal functions

Series implements __array_ufunc__. As part of the implementation, pandas unboxes the ExtensionArray from the *Series*, applies the ufunc, and re-boxes it if necessary.

If applicable, we highly recommend that you implement __array_ufunc__ in your extension array to avoid coercion to an ndarray. See the NumPy documentation for an example.

As part of your implementation, we require that you defer to pandas when a pandas container (*Series*, *DataFrame*, *Index*) is detected in inputs. If any of those is present, you should return NotImplemented. pandas will take care of unboxing the array from the container and re-calling the ufunc with the unwrapped input.

Testing extension arrays

We provide a test suite for ensuring that your extension arrays satisfy the expected behavior. To use the test suite, you must provide several pytest fixtures and inherit from the base test class. The required fixtures are found in https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/conftest.py.

To use a test, subclass it:

```
from pandas.tests.extension import base


class TestConstructors(base.BaseConstructorsTests):
    pass
```

See https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/base/__init__.py for a list of all the tests available.

Compatibility with Apache Arrow

An ExtensionArray can support conversion to / from pyarrow arrays (and thus support for example serialization to the Parquet file format) by implementing two methods: ExtensionArray.__arrow_array__ and ExtensionDtype.__from_arrow__.

The ExtensionArray.__arrow_array__ ensures that pyarrow knowns how to convert the specific extension array into a pyarrow.Array (also when included as a column in a pandas DataFrame):

```
class MyExtensionArray(ExtensionArray):
    ...

    def __arrow_array__(self, type=None):
        # convert the underlying array values to a pyarrow Array
        import pyarrow

        return pyarrow.array(..., type=type)
```

The ExtensionDtype.__from_arrow__ method then controls the conversion back from pyarrow to a pandas ExtensionArray. This method receives a pyarrow Array or ChunkedArray as only argument and is expected to return the appropriate pandas ExtensionArray for this dtype and the passed values:

```
class ExtensionDtype:
    ...

    def __from_arrow__(self, array: pyarrow.Array/ChunkedArray) -> ExtensionArray:
        ...
```

See more in the Arrow documentation.

Those methods have been implemented for the nullable integer and string extension dtypes included in pandas, and ensure roundtrip to pyarrow and the Parquet file format.

4.7.3 Subclassing pandas data structures

Warning: There are some easier alternatives before considering subclassing `pandas` data structures.

1. Extensible method chains with *pipe*
2. Use *composition*. See here.
3. Extending by *registering an accessor*
4. Extending by *extension type*

This section describes how to subclass `pandas` data structures to meet more specific needs. There are two points that need attention:

1. Override constructor properties.
2. Define original properties

Note: You can find a nice example in geopandas project.

Override constructor properties

Each data structure has several *constructor properties* for returning a new data structure as the result of an operation. By overriding these properties, you can retain subclasses through `pandas` data manipulations.

There are 3 constructor properties to be defined:

- `_constructor`: Used when a manipulation result has the same dimensions as the original.
- `_constructor_sliced`: Used when a manipulation result has one lower dimension(s) as the original, such as `DataFrame` single columns slicing.
- `_constructor_expanddim`: Used when a manipulation result has one higher dimension as the original, such as `Series.to_frame()`.

Following table shows how `pandas` data structures define constructor properties by default.

Property Attributes	`Series`	`DataFrame`
`_constructor`	`Series`	`DataFrame`
`_constructor_sliced`	`NotImplementedError`	`Series`
`_constructor_expanddim`	`DataFrame`	`NotImplementedError`

Below example shows how to define `SubclassedSeries` and `SubclassedDataFrame` overriding constructor properties.

```
class SubclassedSeries(pd.Series):
    @property
    def _constructor(self):
```

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```
        return SubclassedSeries

    @property
    def _constructor_expanddim(self):
        return SubclassedDataFrame


class SubclassedDataFrame(pd.DataFrame):
    @property
    def _constructor(self):
        return SubclassedDataFrame

    @property
    def _constructor_sliced(self):
        return SubclassedSeries
```

```
>>> s = SubclassedSeries([1, 2, 3])
>>> type(s)
<class '__main__.SubclassedSeries'>

>>> to_framed = s.to_frame()
>>> type(to_framed)
<class '__main__.SubclassedDataFrame'>

>>> df = SubclassedDataFrame({"A": [1, 2, 3], "B": [4, 5, 6], "C": [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9

>>> type(df)
<class '__main__.SubclassedDataFrame'>

>>> sliced1 = df[["A", "B"]]
>>> sliced1
   A  B
0  1  4
1  2  5
2  3  6

>>> type(sliced1)
<class '__main__.SubclassedDataFrame'>

>>> sliced2 = df["A"]
>>> sliced2
0    1
1    2
2    3
Name: A, dtype: int64

>>> type(sliced2)
<class '__main__.SubclassedSeries'>
```

Define original properties

To let original data structures have additional properties, you should let `pandas` know what properties are added. `pandas` maps unknown properties to data names overriding `__getattribute__`. Defining original properties can be done in one of 2 ways:

1. Define `_internal_names` and `_internal_names_set` for temporary properties which WILL NOT be passed to manipulation results.
2. Define `_metadata` for normal properties which will be passed to manipulation results.

Below is an example to define two original properties, "internal_cache" as a temporary property and "added_property" as a normal property

```
class SubclassedDataFrame2(pd.DataFrame):

    # temporary properties
    _internal_names = pd.DataFrame._internal_names + ["internal_cache"]
    _internal_names_set = set(_internal_names)

    # normal properties
    _metadata = ["added_property"]

    @property
    def _constructor(self):
        return SubclassedDataFrame2
```

```
>>> df = SubclassedDataFrame2({"A": [1, 2, 3], "B": [4, 5, 6], "C": [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9

>>> df.internal_cache = "cached"
>>> df.added_property = "property"

>>> df.internal_cache
cached
>>> df.added_property
property

# properties defined in _internal_names is reset after manipulation
>>> df[["A", "B"]].internal_cache
AttributeError: 'SubclassedDataFrame2' object has no attribute 'internal_cache'

# properties defined in _metadata are retained
>>> df[["A", "B"]].added_property
property
```

4.7.4 Plotting backends

Starting in 0.25 pandas can be extended with third-party plotting backends. The main idea is letting users select a plotting backend different than the provided one based on Matplotlib. For example:

```
>>> pd.set_option("plotting.backend", "backend.module")
>>> pd.Series([1, 2, 3]).plot()
```

This would be more or less equivalent to:

```
>>> import backend.module
>>> backend.module.plot(pd.Series([1, 2, 3]))
```

The backend module can then use other visualization tools (Bokeh, Altair,...) to generate the plots.

Libraries implementing the plotting backend should use entry points to make their backend discoverable to pandas. The key is `"pandas_plotting_backends"`. For example, pandas registers the default "matplotlib" backend as follows.

```
# in setup.py
setup(  # noqa: F821
    ...,
    entry_points={
        "pandas_plotting_backends": [
            "matplotlib = pandas:plotting._matplotlib",
        ],
    },
)
```

More information on how to implement a third-party plotting backend can be found at https://github.com/pandas-dev/pandas/blob/master/pandas/plotting/__init__.py#L1.

4.8 Developer

This section will focus on downstream applications of pandas.

4.8.1 Storing pandas DataFrame objects in Apache Parquet format

The Apache Parquet format provides key-value metadata at the file and column level, stored in the footer of the Parquet file:

```
5: optional list<KeyValue> key_value_metadata
```

where `KeyValue` is

```
struct KeyValue {
  1: required string key
  2: optional string value
}
```

So that a `pandas.DataFrame` can be faithfully reconstructed, we store a `pandas` metadata key in the `FileMetaData` with the value stored as :

```
{'index_columns': [<descr0>, <descr1>, ...],
 'column_indexes': [<ci0>, <ci1>, ..., <ciN>],
 'columns': [<c0>, <c1>, ...],
 'pandas_version': $VERSION,
 'creator': {
   'library': $LIBRARY,
   'version': $LIBRARY_VERSION
 }}
```

The "descriptor" values `<descr0>` in the `'index_columns'` field are strings (referring to a column) or dictionaries with values as described below.

The `<c0>`/`<ci0>` and so forth are dictionaries containing the metadata for each column, *including the index columns*. This has JSON form:

```
{'name': column_name,
 'field_name': parquet_column_name,
 'pandas_type': pandas_type,
 'numpy_type': numpy_type,
 'metadata': metadata}
```

See below for the detailed specification for these.

Index metadata descriptors

`RangeIndex` can be stored as metadata only, not requiring serialization. The descriptor format for these as is follows:

```
index = pd.RangeIndex(0, 10, 2)
{
    "kind": "range",
    "name": index.name,
    "start": index.start,
    "stop": index.stop,
    "step": index.step,
}
```

Other index types must be serialized as data columns along with the other DataFrame columns. The metadata for these is a string indicating the name of the field in the data columns, for example `'__index_level_0__'`.

If an index has a non-None `name` attribute, and there is no other column with a name matching that value, then the `index.name` value can be used as the descriptor. Otherwise (for unnamed indexes and ones with names colliding with other column names) a disambiguating name with pattern matching `__index_level_\d+__` should be used. In cases of named indexes as data columns, `name` attribute is always stored in the column descriptors as above.

Column metadata

`pandas_type` is the logical type of the column, and is one of:

- Boolean: `'bool'`
- Integers: `'int8'`, `'int16'`, `'int32'`, `'int64'`, `'uint8'`, `'uint16'`, `'uint32'`, `'uint64'`
- Floats: `'float16'`, `'float32'`, `'float64'`
- Date and Time Types: `'datetime'`, `'datetimetz'`, `'timedelta'`
- String: `'unicode'`, `'bytes'`

- Categorical: `'categorical'`
- Other Python objects: `'object'`

The `numpy_type` is the physical storage type of the column, which is the result of `str(dtype)` for the underlying NumPy array that holds the data. So for `datetimetz` this is `datetime64[ns]` and for categorical, it may be any of the supported integer categorical types.

The `metadata` field is `None` except for:

- `datetimetz`: `{'timezone': zone, 'unit': 'ns'}`, e.g. `{'timezone', 'America/New_York', 'unit': 'ns'}`. The `'unit'` is optional, and if omitted it is assumed to be nanoseconds.
- `categorical`: `{'num_categories': K, 'ordered': is_ordered, 'type': $TYPE}`
  - Here `'type'` is optional, and can be a nested pandas type specification here (but not categorical)
- `unicode`: `{'encoding': encoding}`
  - The encoding is optional, and if not present is UTF-8
- `object`: `{'encoding': encoding}`. Objects can be serialized and stored in `BYTE_ARRAY` Parquet columns. The encoding can be one of:
  - `'pickle'`
  - `'bson'`
  - `'json'`
- `timedelta`: `{'unit': 'ns'}`. The `'unit'` is optional, and if omitted it is assumed to be nanoseconds. This metadata is optional altogether

For types other than these, the `'metadata'` key can be omitted. Implementations can assume `None` if the key is not present.

As an example of fully-formed metadata:

```
{'index_columns': ['__index_level_0__'],
 'column_indexes': [
     {'name': None,
      'field_name': 'None',
      'pandas_type': 'unicode',
      'numpy_type': 'object',
      'metadata': {'encoding': 'UTF-8'}}
 ],
 'columns': [
     {'name': 'c0',
      'field_name': 'c0',
      'pandas_type': 'int8',
      'numpy_type': 'int8',
      'metadata': None},
     {'name': 'c1',
      'field_name': 'c1',
      'pandas_type': 'bytes',
      'numpy_type': 'object',
      'metadata': None},
     {'name': 'c2',
      'field_name': 'c2',
      'pandas_type': 'categorical',
      'numpy_type': 'int16',
      'metadata': {'num_categories': 1000, 'ordered': False}},
     {'name': 'c3',
```

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```
      'field_name': 'c3',
      'pandas_type': 'datetimetz',
      'numpy_type': 'datetime64[ns]',
      'metadata': {'timezone': 'America/Los_Angeles'}},
     {'name': 'c4',
      'field_name': 'c4',
      'pandas_type': 'object',
      'numpy_type': 'object',
      'metadata': {'encoding': 'pickle'}},
     {'name': None,
      'field_name': '__index_level_0__',
      'pandas_type': 'int64',
      'numpy_type': 'int64',
      'metadata': None}
 ],
 'pandas_version': '0.20.0',
 'creator': {
   'library': 'pyarrow',
   'version': '0.13.0'
 }}
```

4.9 Policies

4.9.1 Version policy

Changed in version 1.0.0.

pandas uses a loose variant of semantic versioning (SemVer) to govern deprecations, API compatibility, and version numbering.

A pandas release number is made up of `MAJOR.MINOR.PATCH`.

API breaking changes should only occur in **major** releases. These changes will be documented, with clear guidance on what is changing, why it's changing, and how to migrate existing code to the new behavior.

Whenever possible, a deprecation path will be provided rather than an outright breaking change.

pandas will introduce deprecations in **minor** releases. These deprecations will preserve the existing behavior while emitting a warning that provide guidance on:

- How to achieve similar behavior if an alternative is available
- The pandas version in which the deprecation will be enforced.

We will not introduce new deprecations in patch releases.

Deprecations will only be enforced in **major** releases. For example, if a behavior is deprecated in pandas 1.2.0, it will continue to work, with a warning, for all releases in the 1.x series. The behavior will change and the deprecation removed in the next major release (2.0.0).

Note: pandas will sometimes make *behavior changing* bug fixes, as part of minor or patch releases. Whether or not a change is a bug fix or an API-breaking change is a judgement call. We'll do our best, and we invite you to participate in development discussion on the issue tracker or mailing list.

These policies do not apply to features marked as **experimental** in the documentation. pandas may change the behavior of experimental features at any time.

4.9.2 Python support

pandas will only drop support for specific Python versions (e.g. 3.6.x, 3.7.x) in pandas **major** or **minor** releases.

4.10 Roadmap

This page provides an overview of the major themes in pandas' development. Each of these items requires a relatively large amount of effort to implement. These may be achieved more quickly with dedicated funding or interest from contributors.

An item being on the roadmap does not mean that it will *necessarily* happen, even with unlimited funding. During the implementation period we may discover issues preventing the adoption of the feature.

Additionally, an item *not* being on the roadmap does not exclude it from inclusion in pandas. The roadmap is intended for larger, fundamental changes to the project that are likely to take months or years of developer time. Smaller-scoped items will continue to be tracked on our issue tracker.

See *Roadmap evolution* for proposing changes to this document.

4.10.1 Extensibility

pandas *Extension types* allow for extending NumPy types with custom data types and array storage. pandas uses extension types internally, and provides an interface for 3rd-party libraries to define their own custom data types.

Many parts of pandas still unintentionally convert data to a NumPy array. These problems are especially pronounced for nested data.

We'd like to improve the handling of extension arrays throughout the library, making their behavior more consistent with the handling of NumPy arrays. We'll do this by cleaning up pandas' internals and adding new methods to the extension array interface.

4.10.2 String data type

Currently, pandas stores text data in an `object` -dtype NumPy array. The current implementation has two primary drawbacks: First, `object` -dtype is not specific to strings: any Python object can be stored in an `object` -dtype array, not just strings. Second: this is not efficient. The NumPy memory model isn't especially well-suited to variable width text data.

To solve the first issue, we propose a new extension type for string data. This will initially be opt-in, with users explicitly requesting `dtype="string"`. The array backing this string dtype may initially be the current implementation: an `object` -dtype NumPy array of Python strings.

To solve the second issue (performance), we'll explore alternative in-memory array libraries (for example, Apache Arrow). As part of the work, we may need to implement certain operations expected by pandas users (for example the algorithm used in, `Series.str.upper`). That work may be done outside of pandas.

4.10.3 Consistent missing value handling

Currently, pandas handles missing data differently for different data types. We use different types to indicate that a value is missing (`np.nan` for floating-point data, `np.nan` or `None` for object-dtype data – typically strings or booleans – with missing values, and `pd.NaT` for datetimelike data). Integer data cannot store missing data or are cast to float. In addition, pandas 1.0 introduced a new missing value sentinel, `pd.NA`, which is being used for the experimental nullable integer, boolean, and string data types.

These different missing values have different behaviors in user-facing operations. Specifically, we introduced different semantics for the nullable data types for certain operations (e.g. propagating in comparison operations instead of comparing as False).

Long term, we want to introduce consistent missing data handling for all data types. This includes consistent behavior in all operations (indexing, arithmetic operations, comparisons, etc.). We want to eventually make the new semantics the default.

This has been discussed at github #28095 (and linked issues), and described in more detail in this design doc.

4.10.4 Apache Arrow interoperability

Apache Arrow is a cross-language development platform for in-memory data. The Arrow logical types are closely aligned with typical pandas use cases.

We'd like to provide better-integrated support for Arrow memory and data types within pandas. This will let us take advantage of its I/O capabilities and provide for better interoperability with other languages and libraries using Arrow.

4.10.5 Block manager rewrite

We'd like to replace pandas current internal data structures (a collection of 1 or 2-D arrays) with a simpler collection of 1-D arrays.

pandas internal data model is quite complex. A DataFrame is made up of one or more 2-dimensional "blocks", with one or more blocks per dtype. This collection of 2-D arrays is managed by the BlockManager.

The primary benefit of the BlockManager is improved performance on certain operations (construction from a 2D array, binary operations, reductions across the columns), especially for wide DataFrames. However, the BlockManager substantially increases the complexity and maintenance burden of pandas.

By replacing the BlockManager we hope to achieve

- Substantially simpler code
- Easier extensibility with new logical types
- Better user control over memory use and layout
- Improved micro-performance
- Option to provide a C / Cython API to pandas' internals

See these design documents for more.

4.10.6 Decoupling of indexing and internals

The code for getting and setting values in pandas' data structures needs refactoring. In particular, we must clearly separate code that converts keys (e.g., the argument to `DataFrame.loc`) to positions from code that uses these positions to get or set values. This is related to the proposed BlockManager rewrite. Currently, the BlockManager sometimes uses label-based, rather than position-based, indexing. We propose that it should only work with positional indexing, and the translation of keys to positions should be entirely done at a higher level.

Indexing is a complicated API with many subtleties. This refactor will require care and attention. More details are discussed at https://github.com/pandas-dev/pandas/wiki/(Tentative)-rules-for-restructuring-indexing-code

4.10.7 Numba-accelerated operations

Numba is a JIT compiler for Python code. We'd like to provide ways for users to apply their own Numba-jitted functions where pandas accepts user-defined functions (for example, `Series.apply()`, `DataFrame.apply()`, `DataFrame.applymap()`, and in groupby and window contexts). This will improve the performance of user-defined-functions in these operations by staying within compiled code.

4.10.8 Performance monitoring

pandas uses airspeed velocity to monitor for performance regressions. ASV itself is a fabulous tool, but requires some additional work to be integrated into an open source project's workflow.

The asv-runner organization, currently made up of pandas maintainers, provides tools built on top of ASV. We have a physical machine for running a number of project's benchmarks, and tools managing the benchmark runs and reporting on results.

We'd like to fund improvements and maintenance of these tools to

- Be more stable. Currently, they're maintained on the nights and weekends when a maintainer has free time.
- Tune the system for benchmarks to improve stability, following https://pyperf.readthedocs.io/en/latest/system.html
- Build a GitHub bot to request ASV runs *before* a PR is merged. Currently, the benchmarks are only run nightly.

4.10.9 Roadmap evolution

pandas continues to evolve. The direction is primarily determined by community interest. Everyone is welcome to review existing items on the roadmap and to propose a new item.

Each item on the roadmap should be a short summary of a larger design proposal. The proposal should include

1. Short summary of the changes, which would be appropriate for inclusion in the roadmap if accepted.
2. Motivation for the changes.
3. An explanation of why the change is in scope for pandas.
4. Detailed design: Preferably with example-usage (even if not implemented yet) and API documentation
5. API Change: Any API changes that may result from the proposal.

That proposal may then be submitted as a GitHub issue, where the pandas maintainers can review and comment on the design. The pandas mailing list should be notified of the proposal.

When there's agreement that an implementation would be welcome, the roadmap should be updated to include the summary and a link to the discussion issue.

4.10.10 Completed items

This section records now completed items from the pandas roadmap.

Documentation improvements

We improved the pandas documentation

- The pandas community worked with others to build the pydata-sphinx-theme, which is now used for https://pandas.pydata.org/docs/ (GH15556).
- *Getting started* contains a number of resources intended for new pandas users coming from a variety of backgrounds (GH26831).

4.11 Developer meetings

We hold regular developer meetings on the second Wednesday of each month at 18:00 UTC. These meetings and their minutes are open to the public. All are welcome to join.

4.11.1 Minutes

The minutes of past meetings are available in this Google Document.

4.11.2 Calendar

This calendar shows all the developer meetings.

You can subscribe to this calendar with the following links:

- iCal
- Google calendar

Additionally, we'll sometimes have one-off meetings on specific topics. These will be published on the same calendar.

CHAPTER

FIVE

RELEASE NOTES

This is the list of changes to pandas between each release. For full details, see the commit logs. For install and upgrade instructions, see *Installation*.

5.1 Version 1.2

5.1.1 What's new in 1.2.2 (February 09, 2021)

These are the changes in pandas 1.2.2. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in *read_excel()* that caused it to raise `AttributeError` when checking version of older xlrd versions (GH38955)
- Fixed regression in *DataFrame* constructor reordering element when construction from datetime ndarray with dtype not `"datetime64[ns]"` (GH39422)
- Fixed regression in *DataFrame.astype()* and *Series.astype()* not casting to bytes dtype (GH39474)
- Fixed regression in *to_pickle()* failing to create bz2/xz compressed pickle files with `protocol=5` (GH39002)
- Fixed regression in *pandas.testing.assert_series_equal()* and *pandas.testing.assert_frame_equal()* always raising `AssertionError` when comparing extension dtypes (GH39410)
- Fixed regression in *to_csv()* opening `codecs.StreamWriter` in binary mode instead of in text mode and ignoring user-provided `mode` (GH39247)
- Fixed regression in `Categorical.astype()` casting to incorrect dtype when `np.int32` is passed to dtype argument (GH39402)
- Fixed regression in *to_excel()* creating corrupt files when appending (`mode="a"`) to an existing file (GH39576)
- Fixed regression in *DataFrame.transform()* failing in case of an empty DataFrame or Series (GH39636)
- Fixed regression in *groupby()* or *resample()* when aggregating an all-NaN or numeric object dtype column (GH39329)
- Fixed regression in *Rolling.count()* where the `min_periods` argument would be set to `0` after the operation (GH39554)

- Fixed regression in *read_excel()* that incorrectly raised when the argument `io` was a non-path and non-buffer and the `engine` argument was specified (GH39528)

Bug fixes

- *pandas.read_excel()* error message when a specified `sheetname` does not exist is now uniform across engines (GH39250)
- Fixed bug in *pandas.read_excel()* producing incorrect results when the engine `openpyxl` is used and the excel file is missing or has incorrect dimension information; the fix requires `openpyxl` >= 3.0.0, prior versions may still fail (GH38956, GH39001)
- Fixed bug in *pandas.read_excel()* sometimes producing a `DataFrame` with trailing rows of `np.nan` when the engine `openpyxl` is used (GH39181)

Contributors

A total of 14 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Andrew Wieteska
- Erfan Nariman
- Joris Van den Bossche
- Matthew Roeschke
- MeeseeksMachine
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- jbrockmendel
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5.1.2 What's new in 1.2.1 (January 20, 2021)

These are the changes in pandas 1.2.1. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in *to_csv()* that created corrupted zip files when there were more rows than chunksize (GH38714)
- Fixed regression in *to_csv()* opening codecs.StreamReaderWriter in binary mode instead of in text mode (GH39247)
- Fixed regression in *read_csv()* and other read functions were the encoding error policy (errors) did not default to "replace" when no encoding was specified (GH38989)
- Fixed regression in *read_excel()* with non-rawbyte file handles (GH38788)
- Fixed regression in *DataFrame.to_stata()* not removing the created file when an error occured (GH39202)
- Fixed regression in DataFrame.__setitem__ raising ValueError when expanding *DataFrame* and new column is from type "0 - name" (GH39010)
- Fixed regression in setting with *DataFrame.loc()* raising ValueError when *DataFrame* has unsorted *MultiIndex* columns and indexer is a scalar (GH38601)
- Fixed regression in setting with *DataFrame.loc()* raising KeyError with *MultiIndex* and list-like columns indexer enlarging *DataFrame* (GH39147)
- Fixed regression in *groupby()* with *Categorical* grouping column not showing unused categories for grouped.indices (GH38642)
- Fixed regression in *GroupBy.sem()* where the presence of non-numeric columns would cause an error instead of being dropped (GH38774)
- Fixed regression in *DataFrameGroupBy.diff()* raising for int8 and int16 columns (GH39050)
- Fixed regression in *DataFrame.groupby()* when aggregating an ExtensionDType that could fail for non-numeric values (GH38980)
- Fixed regression in *Rolling.skew()* and *Rolling.kurt()* modifying the object inplace (GH38908)
- Fixed regression in *DataFrame.any()* and *DataFrame.all()* not returning a result for tz-aware datetime64 columns (GH38723)
- Fixed regression in *DataFrame.apply()* with axis=1 using str accessor in apply function (GH38979)
- Fixed regression in *DataFrame.replace()* raising ValueError when *DataFrame* has dtype bytes (GH38900)
- Fixed regression in *Series.fillna()* that raised RecursionError with datetime64[ns, UTC] dtype (GH38851)
- Fixed regression in comparisons between NaT and datetime.date objects incorrectly returning True (GH39151)
- Fixed regression in calling NumPy accumulate() ufuncs on DataFrames, e.g. np.maximum.accumulate(df) (GH39259)
- Fixed regression in repr of float-like strings of an object dtype having trailing 0's truncated after the decimal (GH38708)
- Fixed regression that raised AttributeError with PyArrow versions [0.16.0, 1.0.0) (GH38801)
- Fixed regression in *pandas.testing.assert_frame_equal()* raising TypeError with check_like=True when *Index* or columns have mixed dtype (GH39168)

We have reverted a commit that resulted in several plotting related regressions in pandas 1.2.0 (GH38969, GH38736, GH38865, GH38947 and GH39126). As a result, bugs reported as fixed in pandas 1.2.0 related to inconsistent tick labeling in bar plots are again present (GH26186 and GH11465)

Calling NumPy ufuncs on non-aligned DataFrames

Before pandas 1.2.0, calling a NumPy ufunc on non-aligned DataFrames (or DataFrame / Series combination) would ignore the indices, only match the inputs by shape, and use the index/columns of the first DataFrame for the result:

```
>>> df1 = pd.DataFrame({"a": [1, 2], "b": [3, 4]}, index=[0, 1])
... df2 = pd.DataFrame({"a": [1, 2], "b": [3, 4]}, index=[1, 2])
>>> df1
   a  b
0  1  3
1  2  4
>>> df2
   a  b
1  1  3
2  2  4

>>> np.add(df1, df2)
   a  b
0  2  6
1  4  8
```

This contrasts with how other pandas operations work, which first align the inputs:

```
>>> df1 + df2
     a    b
0  NaN  NaN
1  3.0  7.0
2  NaN  NaN
```

In pandas 1.2.0, we refactored how NumPy ufuncs are called on DataFrames, and this started to align the inputs first (GH39184), as happens in other pandas operations and as it happens for ufuncs called on Series objects.

For pandas 1.2.1, we restored the previous behaviour to avoid a breaking change, but the above example of `np.add(df1, df2)` with non-aligned inputs will now to raise a warning, and a future pandas 2.0 release will start aligning the inputs first (GH39184). Calling a NumPy ufunc on Series objects (eg `np.add(s1, s2)`) already aligns and continues to do so.

To avoid the warning and keep the current behaviour of ignoring the indices, convert one of the arguments to a NumPy array:

```
>>> np.add(df1, np.asarray(df2))
   a  b
0  2  6
1  4  8
```

To obtain the future behaviour and silence the warning, you can align manually before passing the arguments to the ufunc:

```
>>> df1, df2 = df1.align(df2)
>>> np.add(df1, df2)
     a    b
0  NaN  NaN
```

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```
1  3.0  7.0
2  NaN  NaN
```

Bug fixes

- Bug in *read_csv()* with `float_precision="high"` caused segfault or wrong parsing of long exponent strings. This resulted in a regression in some cases as the default for `float_precision` was changed in pandas 1.2.0 (GH38753)
- Bug in *read_csv()* not closing an opened file handle when a `csv.Error` or `UnicodeDecodeError` occurred while initializing (GH39024)
- Bug in *pandas.testing.assert_index_equal()* raising `TypeError` with `check_order=False` when *Index* has mixed dtype (GH39168)

Other

- The deprecated attributes `_AXIS_NAMES` and `_AXIS_NUMBERS` of *DataFrame* and *Series* will no longer show up in `dir` or `inspect.getmembers` calls (GH38740)
- Bumped minimum fastparquet version to 0.4.0 to avoid `AttributeError` from numba (GH38344)
- Bumped minimum pymysql version to 0.8.1 to avoid test failures (GH38344)
- Fixed build failure on MacOS 11 in Python 3.9.1 (GH38766)
- Added reference to backwards incompatible `check_freq` arg of *testing.assert_frame_equal()* and *testing.assert_series_equal()* in *pandas 1.1.0 whats new* (GH34050)

Contributors

A total of 20 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.1.3 What's new in 1.2.0 (December 26, 2020)

These are the changes in pandas 1.2.0. See *Release notes* for a full changelog including other versions of pandas.

Warning: The xlwt package for writing old-style `.xls` excel files is no longer maintained. The xlrd package is now only for reading old-style `.xls` files.

Previously, the default argument `engine=None` to *`read_excel()`* would result in using the `xlrd` engine in many cases, including new Excel 2007+ (`.xlsx`) files. If openpyxl is installed, many of these cases will now default to using the `openpyxl` engine. See the *`read_excel()`* documentation for more details.

Thus, it is strongly encouraged to install `openpyxl` to read Excel 2007+ (`.xlsx`) files. **Please do not report issues when using ``xlrd`` to read ``.xlsx`` files.** This is no longer supported, switch to using `openpyxl` instead.

Attempting to use the `xlwt` engine will raise a `FutureWarning` unless the option `io.excel.xls.writer` is set to `"xlwt"`. While this option is now deprecated and will also raise a `FutureWarning`, it can be globally set and the warning suppressed. Users are recommended to write `.xlsx` files using the `openpyxl` engine instead.

Enhancements

Optionally disallow duplicate labels

`Series` and *`DataFrame`* can now be created with `allows_duplicate_labels=False` flag to control whether the index or columns can contain duplicate labels (GH28394). This can be used to prevent accidental introduction of duplicate labels, which can affect downstream operations.

By default, duplicates continue to be allowed.

```
In [1]: pd.Series([1, 2], index=['a', 'a'])
Out[1]:
a    1
a    2
Length: 2, dtype: int64

In [2]: pd.Series([1, 2], index=['a', 'a']).set_flags(allows_duplicate_labels=False)
...
DuplicateLabelError: Index has duplicates.
      positions
label
a        [0, 1]
```

pandas will propagate the `allows_duplicate_labels` property through many operations.

```
In [3]: a = (
   ...:     pd.Series([1, 2], index=['a', 'b'])
   ...:       .set_flags(allows_duplicate_labels=False)
   ...: )

In [4]: a
Out[4]:
a    1
b    2
Length: 2, dtype: int64

# An operation introducing duplicates
In [5]: a.reindex(['a', 'b', 'a'])
...
DuplicateLabelError: Index has duplicates.
      positions
label
a        [0, 2]

[1 rows x 1 columns]
```

Warning: This is an experimental feature. Currently, many methods fail to propagate the `allows_duplicate_labels` value. In future versions it is expected that every method taking or returning one or more DataFrame or Series objects will propagate `allows_duplicate_labels`.

See *Duplicate Labels* for more.

The `allows_duplicate_labels` flag is stored in the new *`DataFrame.flags`* attribute. This stores global attributes that apply to the *pandas object*. This differs from *`DataFrame.attrs`*, which stores information that applies to the dataset.

Passing arguments to fsspec backends

Many read/write functions have acquired the `storage_options` optional argument, to pass a dictionary of parameters to the storage backend. This allows, for example, for passing credentials to S3 and GCS storage. The details of what parameters can be passed to which backends can be found in the documentation of the individual storage backends (detailed from the fsspec docs for builtin implementations and linked to external ones). See Section *Reading/writing remote files*.

GH35655 added fsspec support (including `storage_options`) for reading excel files.

Support for binary file handles in `to_csv`

`to_csv()` supports file handles in binary mode (GH19827 and GH35058) with `encoding` (GH13068 and GH23854) and `compression` (GH22555). If pandas does not automatically detect whether the file handle is opened in binary or text mode, it is necessary to provide `mode="wb"`.

For example:

```
In [1]: import io

In [2]: data = pd.DataFrame([0, 1, 2])
```

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```
In [3]: buffer = io.BytesIO()

In [4]: data.to_csv(buffer, encoding="utf-8", compression="gzip")
```

Support for short caption and table position in `to_latex`

DataFrame.to_latex() now allows one to specify a floating table position (GH35281) and a short caption (GH36267).

The keyword `position` has been added to set the position.

```
In [5]: data = pd.DataFrame({'a': [1, 2], 'b': [3, 4]})

In [6]: table = data.to_latex(position='ht')

In [7]: print(table)
\begin{table}[ht]
\centering
\begin{tabular}{lrr}
\toprule
{} &  a &  b \\
\midrule
0 &  1 &  3 \\
1 &  2 &  4 \\
\bottomrule
\end{tabular}
\end{table}
```

Usage of the keyword `caption` has been extended. Besides taking a single string as an argument, one can optionally provide a tuple `(full_caption, short_caption)` to add a short caption macro.

```
In [8]: data = pd.DataFrame({'a': [1, 2], 'b': [3, 4]})

In [9]: table = data.to_latex(caption=('the full long caption', 'short caption'))

In [10]: print(table)
\begin{table}
\centering
\caption[short caption]{the full long caption}
\begin{tabular}{lrr}
\toprule
{} &  a &  b \\
\midrule
0 &  1 &  3 \\
1 &  2 &  4 \\
\bottomrule
\end{tabular}
\end{table}
```

Change in default floating precision for `read_csv` and `read_table`

For the C parsing engine, the methods *`read_csv()`* and *`read_table()`* previously defaulted to a parser that could read floating point numbers slightly incorrectly with respect to the last bit in precision. The option `floating_precision="high"` has always been available to avoid this issue. Beginning with this version, the default is now to use the more accurate parser by making `floating_precision=None` correspond to the high precision parser, and the new option `floating_precision="legacy"` to use the legacy parser. The change to using the higher precision parser by default should have no impact on performance. (GH17154)

Experimental nullable data types for float data

We've added `Float32Dtype` / `Float64Dtype` and `FloatingArray`. These are extension data types dedicated to floating point data that can hold the `pd.NA` missing value indicator (GH32265, GH34307).

While the default float data type already supports missing values using `np.nan`, these new data types use `pd.NA` (and its corresponding behavior) as the missing value indicator, in line with the already existing nullable *integer* and *boolean* data types.

One example where the behavior of `np.nan` and `pd.NA` is different is comparison operations:

```
# the default NumPy float64 dtype
In [11]: s1 = pd.Series([1.5, None])

In [12]: s1
Out[12]:
0    1.5
1    NaN
Length: 2, dtype: float64

In [13]: s1 > 1
Out[13]:
0     True
1    False
Length: 2, dtype: bool
```

```
# the new nullable float64 dtype
In [14]: s2 = pd.Series([1.5, None], dtype="Float64")

In [15]: s2
Out[15]:
0     1.5
1    <NA>
Length: 2, dtype: Float64

In [16]: s2 > 1
Out[16]:
0    True
1    <NA>
Length: 2, dtype: boolean
```

See the *Experimental NA scalar to denote missing values* doc section for more details on the behavior when using the `pd.NA` missing value indicator.

As shown above, the dtype can be specified using the "Float64" or "Float32" string (capitalized to distinguish it from the default "float64" data type). Alternatively, you can also use the dtype object:

```
In [17]: pd.Series([1.5, None], dtype=pd.Float32Dtype())
Out[17]:
0     1.5
1    <NA>
Length: 2, dtype: Float32
```

Operations with the existing integer or boolean nullable data types that give float results will now also use the nullable floating data types (GH38178).

Warning: Experimental: the new floating data types are currently experimental, and their behavior or API may still change without warning. Especially the behavior regarding NaN (distinct from NA missing values) is subject to change.

Index/column name preservation when aggregating

When aggregating using *concat()* or the *DataFrame* constructor, pandas will now attempt to preserve index and column names whenever possible (GH35847). In the case where all inputs share a common name, this name will be assigned to the result. When the input names do not all agree, the result will be unnamed. Here is an example where the index name is preserved:

```
In [18]: idx = pd.Index(range(5), name='abc')

In [19]: ser = pd.Series(range(5, 10), index=idx)

In [20]: pd.concat({'x': ser[1:], 'y': ser[:-1]}, axis=1)
Out[20]:
       x    y
abc
0    NaN  5.0
1    6.0  6.0
2    7.0  7.0
3    8.0  8.0
4    9.0  NaN

[5 rows x 2 columns]
```

The same is true for *MultiIndex*, but the logic is applied separately on a level-by-level basis.

GroupBy supports EWM operations directly

`DataFrameGroupBy` now supports exponentially weighted window operations directly (GH16037).

```
In [21]: df = pd.DataFrame({'A': ['a', 'b', 'a', 'b'], 'B': range(4)})

In [22]: df
Out[22]:
   A  B
0  a  0
1  b  1
2  a  2
3  b  3
```

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```
[4 rows x 2 columns]

In [23]: df.groupby('A').ewm(com=1.0).mean()
Out[23]:
             B
A
a 0  0.000000
  2  1.333333
b 1  1.000000
  3  2.333333

[4 rows x 1 columns]
```

Additionally `mean` supports execution via Numba with the `engine` and `engine_kwargs` arguments. Numba must be installed as an optional dependency to use this feature.

Other enhancements

- Added `day_of_week` (compatibility alias `dayofweek`) property to *`Timestamp`*, *`DatetimeIndex`*, *`Period`*, *`PeriodIndex`* (GH9605)
- Added `day_of_year` (compatibility alias `dayofyear`) property to *`Timestamp`*, *`DatetimeIndex`*, *`Period`*, *`PeriodIndex`* (GH9605)
- Added *`set_flags()`* for setting table-wide flags on a Series or DataFrame (GH28394)
- *`DataFrame.applymap()`* now supports `na_action` (GH23803)
- *`Index`* with object dtype supports division and multiplication (GH34160)
- `io.sql.get_schema()` now supports a `schema` keyword argument that will add a schema into the create table statement (GH28486)
- *`DataFrame.explode()`* and *`Series.explode()`* now support exploding of sets (GH35614)
- *`DataFrame.hist()`* now supports time series (datetime) data (GH32590)
- *`Styler.set_table_styles()`* now allows the direct styling of rows and columns and can be chained (GH35607)
- *`Styler`* now allows direct CSS class name addition to individual data cells (GH36159)
- *`Rolling.mean()`* and *`Rolling.sum()`* use Kahan summation to calculate the mean to avoid numerical problems (GH10319, GH11645, GH13254, GH32761, GH36031)
- `DatetimeIndex.searchsorted()`, `TimedeltaIndex.searchsorted()`, `PeriodIndex.searchsorted()`, and *`Series.searchsorted()`* with datetime-like dtypes will now try to cast string arguments (list-like and scalar) to the matching datetime-like type (GH36346)
- Added methods `IntegerArray.prod()`, `IntegerArray.min()`, and `IntegerArray.max()` (GH33790)
- Calling a NumPy ufunc on a `DataFrame` with extension types now preserves the extension types when possible (GH23743)
- Calling a binary-input NumPy ufunc on multiple `DataFrame` objects now aligns, matching the behavior of binary operations and ufuncs on `Series` (GH23743). This change has been reverted in pandas 1.2.1, and the behaviour to not align DataFrames is deprecated instead, see the *the 1.2.1 release notes*.

- Where possible `RangeIndex.difference()` and `RangeIndex.symmetric_difference()` will return *`RangeIndex`* instead of *`Int64Index`* (GH36564)
- *`DataFrame.to_parquet()`* now supports *`MultiIndex`* for columns in parquet format (GH34777)
- *`read_parquet()`* gained a `use_nullable_dtypes=True` option to use nullable dtypes that use `pd.NA` as missing value indicator where possible for the resulting DataFrame (default is `False`, and only applicable for `engine="pyarrow"`) (GH31242)
- Added *`Rolling.sem()`* and `Expanding.sem()` to compute the standard error of the mean (GH26476)
- *`Rolling.var()`* and *`Rolling.std()`* use Kahan summation and Welford's Method to avoid numerical issues (GH37051)
- *`DataFrame.corr()`* and *`DataFrame.cov()`* use Welford's Method to avoid numerical issues (GH37448)
- *`DataFrame.plot()`* now recognizes `xlabel` and `ylabel` arguments for plots of type `scatter` and `hexbin` (GH37001)
- *`DataFrame`* now supports the `divmod` operation (GH37165)
- *`DataFrame.to_parquet()`* now returns a `bytes` object when no `path` argument is passed (GH37105)
- `Rolling` now supports the `closed` argument for fixed windows (GH34315)
- *`DatetimeIndex`* and *`Series`* with `datetime64` or `datetime64tz` dtypes now support `std` (GH37436)
- `Window` now supports all Scipy window types in `win_type` with flexible keyword argument support (GH34556)
- *`testing.assert_index_equal()`* now has a `check_order` parameter that allows indexes to be checked in an order-insensitive manner (GH37478)
- *`read_csv()`* supports memory-mapping for compressed files (GH37621)
- Add support for `min_count` keyword for *`DataFrame.groupby()`* and *`DataFrame.resample()`* for functions `min`, `max`, `first` and `last` (GH37821, GH37768)
- Improve error reporting for *`DataFrame.merge()`* when invalid merge column definitions were given (GH16228)
- Improve numerical stability for *`Rolling.skew()`*, *`Rolling.kurt()`*, `Expanding.skew()` and `Expanding.kurt()` through implementation of Kahan summation (GH6929)
- Improved error reporting for subsetting columns of a `DataFrameGroupBy` with `axis=1` (GH37725)
- Implement method `cross` for *`DataFrame.merge()`* and *`DataFrame.join()`* (GH5401)
- When *`read_csv()`*, *`read_sas()`* and *`read_json()`* are called with `chunksize`/`iterator` they can be used in a `with` statement as they return context-managers (GH38225)
- Augmented the list of named colors available for styling Excel exports, enabling all of CSS4 colors (GH38247)

Notable bug fixes

These are bug fixes that might have notable behavior changes.

Consistency of DataFrame Reductions

DataFrame.any() and *DataFrame.all()* with `bool_only=True` now determines whether to exclude object-dtype columns on a column-by-column basis, instead of checking if *all* object-dtype columns can be considered boolean.

This prevents pathological behavior where applying the reduction on a subset of columns could result in a larger Series result. See (GH37799).

```
In [24]: df = pd.DataFrame({"A": ["foo", "bar"], "B": [True, False]}, dtype=object)

In [25]: df["C"] = pd.Series([True, True])
```

Previous behavior:

```
In [5]: df.all(bool_only=True)
Out[5]:
C    True
dtype: bool

In [6]: df[["B", "C"]].all(bool_only=True)
Out[6]:
B    False
C    True
dtype: bool
```

New behavior:

```
In [26]: In [5]: df.all(bool_only=True)
Out[26]:
B    False
C     True
Length: 2, dtype: bool

In [27]: In [6]: df[["B", "C"]].all(bool_only=True)
Out[27]:
B    False
C     True
Length: 2, dtype: bool
```

Other DataFrame reductions with `numeric_only=None` will also avoid this pathological behavior (GH37827):

```
In [28]: df = pd.DataFrame({"A": [0, 1, 2], "B": ["a", "b", "c"]}, dtype=object)
```

Previous behavior:

```
In [3]: df.mean()
Out[3]: Series([], dtype: float64)

In [4]: df[["A"]].mean()
Out[4]:
A    1.0
dtype: float64
```

New behavior:

```
In [29]: df.mean()
Out[29]:
A    1.0
Length: 1, dtype: float64

In [30]: df[["A"]].mean()
Out[30]:
A    1.0
Length: 1, dtype: float64
```

Moreover, DataFrame reductions with `numeric_only=None` will now be consistent with their Series counterparts. In particular, for reductions where the Series method raises `TypeError`, the DataFrame reduction will now consider that column non-numeric instead of casting to a NumPy array which may have different semantics (GH36076, GH28949, GH21020).

```
In [31]: ser = pd.Series([0, 1], dtype="category", name="A")

In [32]: df = ser.to_frame()
```

Previous behavior:

```
In [5]: df.any()
Out[5]:
A    True
dtype: bool
```

New behavior:

```
In [33]: df.any()
Out[33]: Series([], Length: 0, dtype: bool)
```

Increased minimum version for Python

pandas 1.2.0 supports Python 3.7.1 and higher (GH35214).

Increased minimum versions for dependencies

Some minimum supported versions of dependencies were updated (GH35214). If installed, we now require:

Package	Minimum Version	Required	Changed
numpy	1.16.5	X	X
pytz	2017.3	X	X
python-dateutil	2.7.3	X	
bottleneck	1.2.1		
numexpr	2.6.8		X
pytest (dev)	5.0.1		X
mypy (dev)	0.782		X

For optional libraries the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

Package	Minimum Version	Changed
beautifulsoup4	4.6.0	
fastparquet	0.3.2	
fsspec	0.7.4	
gcsfs	0.6.0	
lxml	4.3.0	X
matplotlib	2.2.3	X
numba	0.46.0	
openpyxl	2.6.0	X
pyarrow	0.15.0	X
pymysql	0.7.11	X
pytables	3.5.1	X
s3fs	0.4.0	
scipy	1.2.0	
sqlalchemy	1.2.8	X
xarray	0.12.3	X
xlrd	1.2.0	X
xlsxwriter	1.0.2	X
xlwt	1.3.0	X
pandas-gbq	0.12.0	

See *Dependencies* and *Optional dependencies* for more.

Other API changes

- Sorting in descending order is now stable for *Series.sort_values()* and *Index.sort_values()* for Datetime-like *Index* subclasses. This will affect sort order when sorting a DataFrame on multiple columns, sorting with a key function that produces duplicates, or requesting the sorting index when using *Index.sort_values()*. When using *Series.value_counts()*, the count of missing values is no longer necessarily last in the list of duplicate counts. Instead, its position corresponds to the position in the original Series. When using *Index.sort_values()* for Datetime-like *Index* subclasses, NaTs ignored the `na_position` argument and were sorted to the beginning. Now they respect `na_position`, the default being `last`, same as other *Index* subclasses (GH35992)
- Passing an invalid `fill_value` to `Categorical.take()`, `DatetimeArray.take()`, `TimedeltaArray.take()`, or `PeriodArray.take()` now raises a `TypeError` instead of a `ValueError` (GH37733)
- Passing an invalid `fill_value` to *Series.shift()* with a `CategoricalDtype` now raises a `TypeError` instead of a `ValueError` (GH37733)
- Passing an invalid value to `IntervalIndex.insert()` or `CategoricalIndex.insert()` now raises a `TypeError` instead of a `ValueError` (GH37733)
- Attempting to reindex a Series with a *CategoricalIndex* with an invalid `fill_value` now raises a `TypeError` instead of a `ValueError` (GH37733)
- `CategoricalIndex.append()` with an index that contains non-category values will now cast instead of raising `TypeError` (GH38098)

Deprecations

- Deprecated parameter `inplace` in *MultiIndex.set_codes()* and *MultiIndex.set_levels()* (GH35626)
- Deprecated parameter `dtype` of method *copy()* for all *Index* subclasses. Use the *astype()* method instead for changing dtype (GH35853)
- Deprecated parameters `levels` and `codes` in `MultiIndex.copy()`. Use the *set_levels()* and *set_codes()* methods instead (GH36685)
- Date parser functions `parse_date_time()`, `parse_date_fields()`, `parse_all_fields()` and `generic_parser()` from `pandas.io.date_converters` are deprecated and will be removed in a future version; use *to_datetime()* instead (GH35741)
- *DataFrame.lookup()* is deprecated and will be removed in a future version, use *DataFrame.melt()* and *DataFrame.loc()* instead (GH35224)
- The method *Index.to_native_types()* is deprecated. Use `.astype(str)` instead (GH28867)
- Deprecated indexing *DataFrame* rows with a single datetime-like string as `df[string]` (given the ambiguity whether it is indexing the rows or selecting a column), use `df.loc[string]` instead (GH36179)
- Deprecated *Index.is_all_dates()* (GH27744)
- The default value of `regex` for *Series.str.replace()* will change from `True` to `False` in a future release. In addition, single character regular expressions will *not* be treated as literal strings when `regex=True` is set (GH24804)
- Deprecated automatic alignment on comparison operations between *DataFrame* and *Series*, do `frame, ser = frame.align(ser, axis=1, copy=False)` before e.g. `frame == ser` (GH28759)
- `Rolling.count()` with `min_periods=None` will default to the size of the window in a future version (GH31302)
- Using "outer" ufuncs on DataFrames to return 4d ndarray is now deprecated. Convert to an ndarray first (GH23743)
- Deprecated slice-indexing on tz-aware *DatetimeIndex* with naive `datetime` objects, to match scalar indexing behavior (GH36148)
- *Index.ravel()* returning a `np.ndarray` is deprecated, in the future this will return a view on the same index (GH19956)
- Deprecate use of strings denoting units with 'M', 'Y' or 'y' in *to_timedelta()* (GH36666)
- *Index* methods `&`, `|`, and `^` behaving as the set operations *Index.intersection()*, *Index.union()*, and *Index.symmetric_difference()*, respectively, are deprecated and in the future will behave as pointwise boolean operations matching *Series* behavior. Use the named set methods instead (GH36758)
- `Categorical.is_dtype_equal()` and `CategoricalIndex.is_dtype_equal()` are deprecated, will be removed in a future version (GH37545)
- *Series.slice_shift()* and *DataFrame.slice_shift()* are deprecated, use *Series.shift()* or *DataFrame.shift()* instead (GH37601)
- Partial slicing on unordered *DatetimeIndex* objects with keys that are not in the index is deprecated and will be removed in a future version (GH18531)
- The `how` keyword in `PeriodIndex.astype()` is deprecated and will be removed in a future version, use `index.to_timestamp(how=how)` instead (GH37982)
- Deprecated *Index.asi8()* for *Index* subclasses other than *DatetimeIndex*, *TimedeltaIndex*, and *PeriodIndex* (GH37877)

- The `inplace` parameter of `Categorical.remove_unused_categories()` is deprecated and will be removed in a future version (GH37643)
- The `null_counts` parameter of *`DataFrame.info()`* is deprecated and replaced by `show_counts`. It will be removed in a future version (GH37999)

Calling NumPy ufuncs on non-aligned DataFrames

Calling NumPy ufuncs on non-aligned DataFrames changed behaviour in pandas 1.2.0 (to align the inputs before calling the ufunc), but this change is reverted in pandas 1.2.1. The behaviour to not align is now deprecated instead, see the *the 1.2.1 release notes* for more details.

Performance improvements

- Performance improvements when creating DataFrame or Series with dtype `str` or *`StringDtype`* from array with many string elements (GH36304, GH36317, GH36325, GH36432, GH37371)
- Performance improvement in *`GroupBy.agg()`* with the `numba` engine (GH35759)
- Performance improvements when creating *`Series.map()`* from a huge dictionary (GH34717)
- Performance improvement in `GroupBy.transform()` with the `numba` engine (GH36240)
- *`Styler`* uuid method altered to compress data transmission over web whilst maintaining reasonably low table collision probability (GH36345)
- Performance improvement in *`to_datetime()`* with non-ns time unit for `float` `dtype` columns (GH20445)
- Performance improvement in setting values on an `IntervalArray` (GH36310)
- The internal index method `_shallow_copy()` now makes the new index and original index share cached attributes, avoiding creating these again, if created on either. This can speed up operations that depend on creating copies of existing indexes (GH36840)
- Performance improvement in `RollingGroupby.count()` (GH35625)
- Small performance decrease to *`Rolling.min()`* and *`Rolling.max()`* for fixed windows (GH36567)
- Reduced peak memory usage in *`DataFrame.to_pickle()`* when using `protocol=5` in python 3.8+ (GH34244)
- Faster `dir` calls when the object has many index labels, e.g. `dir(ser)` (GH37450)
- Performance improvement in `ExpandingGroupby` (GH37064)
- Performance improvement in *`Series.astype()`* and *`DataFrame.astype()`* for *`Categorical`* (GH8628)
- Performance improvement in *`DataFrame.groupby()`* for `float` `dtype` (GH28303), changes of the underlying hash-function can lead to changes in float based indexes sort ordering for ties (e.g. *`Index.value_counts()`*)
- Performance improvement in `pd.isin()` for inputs with more than 1e6 elements (GH36611)
- Performance improvement for `DataFrame.__setitem__()` with list-like indexers (GH37954)
- *`read_json()`* now avoids reading entire file into memory when chunksize is specified (GH34548)

Bug fixes

Categorical

- `Categorical.fillna()` will always return a copy, validate a passed fill value regardless of whether there are any NAs to fill, and disallow an `NaT` as a fill value for numeric categories (GH36530)
- Bug in `Categorical.__setitem__()` that incorrectly raised when trying to set a tuple value (GH20439)
- Bug in *`CategoricalIndex.equals()`* incorrectly casting non-category entries to `np.nan` (GH37667)
- Bug in `CategoricalIndex.where()` incorrectly setting non-category entries to `np.nan` instead of raising `TypeError` (GH37977)
- Bug in `Categorical.to_numpy()` and `np.array(categorical)` with tz-aware `datetime64` categories incorrectly dropping the time zone information instead of casting to object dtype (GH38136)

Datetime-like

- Bug in *`DataFrame.combine_first()`* that would convert datetime-like column on other *`DataFrame`* to integer when the column is not present in original *`DataFrame`* (GH28481)
- Bug in `DatetimeArray.date` where a `ValueError` would be raised with a read-only backing array (GH33530)
- Bug in `NaT` comparisons failing to raise `TypeError` on invalid inequality comparisons (GH35046)
- Bug in *`DateOffset`* where attributes reconstructed from pickle files differ from original objects when input values exceed normal ranges (e.g. months=12) (GH34511)
- Bug in `DatetimeIndex.get_slice_bound()` where `datetime.date` objects were not accepted or naive *`Timestamp`* with a tz-aware *`DatetimeIndex`* (GH35690)
- Bug in `DatetimeIndex.slice_locs()` where `datetime.date` objects were not accepted (GH34077)
- Bug in `DatetimeIndex.searchsorted()`, `TimedeltaIndex.searchsorted()`, `PeriodIndex.searchsorted()`, and *`Series.searchsorted()`* with `datetime64`, `timedelta64` or *`Period`* dtype placement of `NaT` values being inconsistent with NumPy (GH36176, GH36254)
- Inconsistency in *`DatetimeArray`*, *`TimedeltaArray`*, and *`PeriodArray`* method `__setitem__` casting arrays of strings to datetime-like scalars but not scalar strings (GH36261)
- Bug in `DatetimeArray.take()` incorrectly allowing `fill_value` with a mismatched time zone (GH37356)
- Bug in `DatetimeIndex.shift` incorrectly raising when shifting empty indexes (GH14811)
- *`Timestamp`* and *`DatetimeIndex`* comparisons between tz-aware and tz-naive objects now follow the standard library `datetime` behavior, returning `True`/`False` for `!=`/`==` and raising for inequality comparisons (GH28507)
- Bug in `DatetimeIndex.equals()` and `TimedeltaIndex.equals()` incorrectly considering `int64` indexes as equal (GH36744)
- *`Series.to_json()`*, *`DataFrame.to_json()`*, and *`read_json()`* now implement time zone parsing when orient structure is `table` (GH35973)
- `astype()` now attempts to convert to `datetime64[ns, tz]` directly from `object` with inferred time zone from string (GH35973)

- Bug in `TimedeltaIndex.sum()` and *`Series.sum()`* with `timedelta64` dtype on an empty index or series returning `NaT` instead of `Timedelta(0)` (GH31751)
- Bug in `DatetimeArray.shift()` incorrectly allowing `fill_value` with a mismatched time zone (GH37299)
- Bug in adding a *`BusinessDay`* with nonzero `offset` to a non-scalar other (GH37457)
- Bug in *`to_datetime()`* with a read-only array incorrectly raising (GH34857)
- Bug in *`Series.isin()`* with `datetime64[ns]` dtype and `DatetimeIndex.isin()` incorrectly casting integers to datetimes (GH36621)
- Bug in *`Series.isin()`* with `datetime64[ns]` dtype and `DatetimeIndex.isin()` failing to consider tz-aware and tz-naive datetimes as always different (GH35728)
- Bug in *`Series.isin()`* with `PeriodDtype` dtype and `PeriodIndex.isin()` failing to consider arguments with different `PeriodDtype` as always different (GH37528)
- Bug in *`Period`* constructor now correctly handles nanoseconds in the `value` argument (GH34621 and GH17053)

Timedelta

- Bug in *`TimedeltaIndex`*, *`Series`*, and *`DataFrame`* floor-division with `timedelta64` dtypes and `NaT` in the denominator (GH35529)
- Bug in parsing of ISO 8601 durations in *`Timedelta`* and *`to_datetime()`* (GH29773, GH36204)
- Bug in *`to_timedelta()`* with a read-only array incorrectly raising (GH34857)
- Bug in *`Timedelta`* incorrectly truncating to sub-second portion of a string input when it has precision higher than nanoseconds (GH36738)

Timezones

- Bug in *`date_range()`* was raising `AmbiguousTimeError` for valid input with `ambiguous=False` (GH35297)
- Bug in *`Timestamp.replace()`* was losing fold information (GH37610)

Numeric

- Bug in *`to_numeric()`* where float precision was incorrect (GH31364)
- Bug in *`DataFrame.any()`* with `axis=1` and `bool_only=True` ignoring the `bool_only` keyword (GH32432)
- Bug in *`Series.equals()`* where a `ValueError` was raised when NumPy arrays were compared to scalars (GH35267)
- Bug in *`Series`* where two Series each have a *`DatetimeIndex`* with different time zones having those indexes incorrectly changed when performing arithmetic operations (GH33671)
- Bug in `pandas.testing` module functions when used with `check_exact=False` on complex numeric types (GH28235)
- Bug in `DataFrame.__rmatmul__()` error handling reporting transposed shapes (GH21581)

- Bug in *Series* flex arithmetic methods where the result when operating with a `list`, `tuple` or `np.ndarray` would have an incorrect name (GH36760)
- Bug in *IntegerArray* multiplication with `timedelta` and `np.timedelta64` objects (GH36870)
- Bug in *MultiIndex* comparison with tuple incorrectly treating tuple as array-like (GH21517)
- Bug in *DataFrame.diff()* with `datetime64` dtypes including `NaT` values failing to fill `NaT` results correctly (GH32441)
- Bug in *DataFrame* arithmetic ops incorrectly accepting keyword arguments (GH36843)
- Bug in *IntervalArray* comparisons with *Series* not returning Series (GH36908)
- Bug in *DataFrame* allowing arithmetic operations with list of array-likes with undefined results. Behavior changed to raising `ValueError` (GH36702)
- Bug in *DataFrame.std()* with `timedelta64` dtype and `skipna=False` (GH37392)
- Bug in *DataFrame.min()* and *DataFrame.max()* with `datetime64` dtype and `skipna=False` (GH36907)
- Bug in *DataFrame.idxmax()* and *DataFrame.idxmin()* with mixed dtypes incorrectly raising `TypeError` (GH38195)

Conversion

- Bug in *DataFrame.to_dict()* with `orient='records'` now returns python native datetime objects for datetime-like columns (GH21256)
- Bug in *Series.astype()* conversion from `string` to `float` raised in presence of `pd.NA` values (GH37626)

Strings

- Bug in *Series.to_string()*, *DataFrame.to_string()*, and *DataFrame.to_latex()* adding a leading space when `index=False` (GH24980)
- Bug in *to_numeric()* raising a `TypeError` when attempting to convert a string dtype Series containing only numeric strings and `NA` (GH37262)

Interval

- Bug in *DataFrame.replace()* and *Series.replace()* where *Interval* dtypes would be converted to object dtypes (GH34871)
- Bug in `IntervalIndex.take()` with negative indices and `fill_value=None` (GH37330)
- Bug in `IntervalIndex.putmask()` with datetime-like dtype incorrectly casting to object dtype (GH37968)
- Bug in `IntervalArray.astype()` incorrectly dropping dtype information with a *CategoricalDtype* object (GH37984)

Indexing

- Bug in `PeriodIndex.get_loc()` incorrectly raising `ValueError` on non-datelike strings instead of `KeyError`, causing similar errors in `Series.__getitem__()`, `Series.__contains__()`, and `Series.loc.__getitem__()` (GH34240)
- Bug in *`Index.sort_values()`* where, when empty values were passed, the method would break by trying to compare missing values instead of pushing them to the end of the sort order (GH35584)
- Bug in *`Index.get_indexer()`* and *`Index.get_indexer_non_unique()`* where `int64` arrays are returned instead of `intp` (GH36359)
- Bug in *`DataFrame.sort_index()`* where parameter ascending passed as a list on a single level index gives wrong result (GH32334)
- Bug in *`DataFrame.reset_index()`* was incorrectly raising a `ValueError` for input with a *`MultiIndex`* with missing values in a level with `Categorical` dtype (GH24206)
- Bug in indexing with boolean masks on datetime-like values sometimes returning a view instead of a copy (GH36210)
- Bug in `DataFrame.__getitem__()` and `DataFrame.loc.__getitem__()` with *`IntervalIndex`* columns and a numeric indexer (GH26490)
- Bug in `Series.loc.__getitem__()` with a non-unique *`MultiIndex`* and an empty-list indexer (GH13691)
- Bug in indexing on a *`Series`* or *`DataFrame`* with a *`MultiIndex`* and a level named `"0"` (GH37194)
- Bug in `Series.__getitem__()` when using an unsigned integer array as an indexer giving incorrect results or segfaulting instead of raising `KeyError` (GH37218)
- Bug in *`Index.where()`* incorrectly casting numeric values to strings (GH37591)
- Bug in *`DataFrame.loc()`* returning empty result when indexer is a slice with negative step size (GH38071)
- Bug in *`Series.loc()`* and *`DataFrame.loc()`* raises when the index was of `object` dtype and the given numeric label was in the index (GH26491)
- Bug in *`DataFrame.loc()`* returned requested key plus missing values when `loc` was applied to single level from a *`MultiIndex`* (GH27104)
- Bug in indexing on a *`Series`* or *`DataFrame`* with a *`CategoricalIndex`* using a list-like indexer containing NA values (GH37722)
- Bug in `DataFrame.loc.__setitem__()` expanding an empty *`DataFrame`* with mixed dtypes (GH37932)
- Bug in *`DataFrame.xs()`* ignored `droplevel=False` for columns (GH19056)
- Bug in *`DataFrame.reindex()`* raising `IndexingError` wrongly for empty DataFrame with `tolerance` not `None` or `method="nearest"` (GH27315)
- Bug in indexing on a *`Series`* or *`DataFrame`* with a *`CategoricalIndex`* using list-like indexer that contains elements that are in the index's `categories` but not in the index itself failing to raise `KeyError` (GH37901)
- Bug on inserting a boolean label into a *`DataFrame`* with a numeric *`Index`* columns incorrectly casting to integer (GH36319)
- Bug in *`DataFrame.iloc()`* and *`Series.iloc()`* aligning objects in `__setitem__` (GH22046)
- Bug in `MultiIndex.drop()` does not raise if labels are partially found (GH37820)

- Bug in *DataFrame.loc()* did not raise KeyError when missing combination was given with slice(None) for remaining levels (GH19556)
- Bug in *DataFrame.loc()* raising TypeError when non-integer slice was given to select values from *MultiIndex* (GH25165, GH24263)
- Bug in *Series.at()* returning *Series* with one element instead of scalar when index is a *MultiIndex* with one level (GH38053)
- Bug in *DataFrame.loc()* returning and assigning elements in wrong order when indexer is differently ordered than the *MultiIndex* to filter (GH31330, GH34603)
- Bug in *DataFrame.loc()* and DataFrame.__getitem__() raising KeyError when columns were *MultiIndex* with only one level (GH29749)
- Bug in Series.__getitem__() and DataFrame.__getitem__() raising blank KeyError without missing keys for *IntervalIndex* (GH27365)
- Bug in setting a new label on a *DataFrame* or *Series* with a *CategoricalIndex* incorrectly raising TypeError when the new label is not among the index's categories (GH38098)
- Bug in *Series.loc()* and *Series.iloc()* raising ValueError when inserting a list-like np.array, list or tuple in an object Series of equal length (GH37748, GH37486)
- Bug in *Series.loc()* and *Series.iloc()* setting all the values of an object Series with those of a list-like ExtensionArray instead of inserting it (GH38271)

Missing

- Bug in *SeriesGroupBy.transform()* now correctly handles missing values for dropna=False (GH35014)
- Bug in *Series.nunique()* with dropna=True was returning incorrect results when both NA and None missing values were present (GH37566)
- Bug in *Series.interpolate()* where kwarg limit_area and limit_direction had no effect when using methods pad and backfill (GH31048)

MultiIndex

- Bug in *DataFrame.xs()* when used with *IndexSlice* raises TypeError with message "Expected label or tuple of labels" (GH35301)
- Bug in *DataFrame.reset_index()* with NaT values in index raises ValueError with message "cannot convert float NaN to integer" (GH36541)
- Bug in *DataFrame.combine_first()* when used with *MultiIndex* containing string and NaN values raises TypeError (GH36562)
- Bug in MultiIndex.drop() dropped NaN values when non existing key was given as input (GH18853)
- Bug in MultiIndex.drop() dropping more values than expected when index has duplicates and is not sorted (GH33494)

I/O

- *read_sas()* no longer leaks resources on failure (GH35566)
- Bug in *DataFrame.to_csv()* and *Series.to_csv()* caused a ValueError when it was called with a filename in combination with mode containing a b (GH35058)
- Bug in *read_csv()* with float_precision='round_trip' did not handle decimal and thousands parameters (GH35365)
- to_pickle() and *read_pickle()* were closing user-provided file objects (GH35679)
- to_csv() passes compression arguments for 'gzip' always to gzip.GzipFile (GH28103)
- to_csv() did not support zip compression for binary file object not having a filename (GH35058)
- to_csv() and *read_csv()* did not honor compression and encoding for path-like objects that are internally converted to file-like objects (GH35677, GH26124, GH32392)
- *DataFrame.to_pickle()*, *Series.to_pickle()*, and *read_pickle()* did not support compression for file-objects (GH26237, GH29054, GH29570)
- Bug in LongTableBuilder.middle_separator() was duplicating LaTeX longtable entries in the List of Tables of a LaTeX document (GH34360)
- Bug in *read_csv()* with engine='python' truncating data if multiple items present in first row and first element started with BOM (GH36343)
- Removed private_key and verbose from *read_gbq()* as they are no longer supported in pandas-gbq (GH34654, GH30200)
- Bumped minimum pytables version to 3.5.1 to avoid a ValueError in *read_hdf()* (GH24839)
- Bug in *read_table()* and *read_csv()* when delim_whitespace=True and sep=default (GH36583)
- Bug in *DataFrame.to_json()* and *Series.to_json()* when used with lines=True and orient='records' the last line of the record is not appended with 'new line character' (GH36888)
- Bug in *read_parquet()* with fixed offset time zones. String representation of time zones was not recognized (GH35997, GH36004)
- Bug in *DataFrame.to_html()*, *DataFrame.to_string()*, and *DataFrame.to_latex()* ignoring the na_rep argument when float_format was also specified (GH9046, GH13828)
- Bug in output rendering of complex numbers showing too many trailing zeros (GH36799)
- Bug in HDFStore threw a TypeError when exporting an empty DataFrame with datetime64[ns, tz] dtypes with a fixed HDF5 store (GH20594)
- Bug in HDFStore was dropping time zone information when exporting a Series with datetime64[ns, tz] dtypes with a fixed HDF5 store (GH20594)
- *read_csv()* was closing user-provided binary file handles when engine="c" and an encoding was requested (GH36980)
- Bug in *DataFrame.to_hdf()* was not dropping missing rows with dropna=True (GH35719)
- Bug in *read_html()* was raising a TypeError when supplying a pathlib.Path argument to the io parameter (GH37705)
- *DataFrame.to_excel()*, *Series.to_excel()*, *DataFrame.to_markdown()*, and *Series.to_markdown()* now support writing to fsspec URLs such as S3 and Google Cloud Storage (GH33987)
- Bug in *read_fwf()* with skip_blank_lines=True was not skipping blank lines (GH37758)

- Parse missing values using *read_json()* with `dtype=False` to `NaN` instead of `None` (GH28501)
- *read_fwf()* was inferring compression with `compression=None` which was not consistent with the other `read_*` functions (GH37909)
- *DataFrame.to_html()* was ignoring `formatters` argument for `ExtensionDtype` columns (GH36525)
- Bumped minimum xarray version to 0.12.3 to avoid reference to the removed `Panel` class (GH27101, GH37983)
- *DataFrame.to_csv()* was re-opening file-like handles that also implement `os.PathLike` (GH38125)
- Bug in the conversion of a sliced `pyarrow.Table` with missing values to a DataFrame (GH38525)
- Bug in *read_sql_table()* raising a `sqlalchemy.exc.OperationalError` when column names contained a percentage sign (GH37517)

Period

- Bug in *DataFrame.replace()* and *Series.replace()* where *Period* dtypes would be converted to object dtypes (GH34871)

Plotting

- Bug in *DataFrame.plot()* was rotating xticklabels when `subplots=True`, even if the x-axis wasn't an irregular time series (GH29460)
- Bug in *DataFrame.plot()* where a marker letter in the `style` keyword sometimes caused a `ValueError` (GH21003)
- Bug in *DataFrame.plot.bar()* and *Series.plot.bar()* where ticks positions were assigned by value order instead of using the actual value for numeric or a smart ordering for string (GH26186, GH11465). This fix has been reverted in pandas 1.2.1, see *What's new in 1.2.1 (January 20, 2021)*
- Twinned axes were losing their tick labels which should only happen to all but the last row or column of 'externally' shared axes (GH33819)
- Bug in *Series.plot()* and *DataFrame.plot()* was throwing a `ValueError` when the Series or DataFrame was indexed by a *TimedeltaIndex* with a fixed frequency and the x-axis lower limit was greater than the upper limit (GH37454)
- Bug in *DataFrameGroupBy.boxplot()* when `subplots=False` would raise a `KeyError` (GH16748)
- Bug in *DataFrame.plot()* and *Series.plot()* was overwriting matplotlib's shared y axes behavior when no `sharey` parameter was passed (GH37942)
- Bug in *DataFrame.plot()* was raising a `TypeError` with `ExtensionDtype` columns (GH32073)

Styler

- Bug in `Styler.render()` HTML was generated incorrectly because of formatting error in `rowspan` attribute, it now matches with w3 syntax (GH38234)

Groupby/resample/rolling

- Bug in *`DataFrameGroupBy.count()`* and `SeriesGroupBy.sum()` returning `NaN` for missing categories when grouped on multiple `Categoricals`. Now returning `0` (GH35028)
- Bug in `DataFrameGroupBy.apply()` that would sometimes throw an erroneous `ValueError` if the grouping axis had duplicate entries (GH16646)
- Bug in *`DataFrame.resample()`* that would throw a `ValueError` when resampling from `"D"` to `"24H"` over a transition into daylight savings time (DST) (GH35219)
- Bug when combining methods *`DataFrame.groupby()`* with *`DataFrame.resample()`* and *`DataFrame.interpolate()`* raising a `TypeError` (GH35325)
- Bug in `DataFrameGroupBy.apply()` where a non-nuisance grouping column would be dropped from the output columns if another groupby method was called before `.apply` (GH34656)
- Bug when subsetting columns on a `DataFrameGroupBy` (e.g. `df.groupby('a')[['b']]`) would reset the attributes `axis`, `dropna`, `group_keys`, `level`, `mutated`, `sort`, and `squeeze` to their default values (GH9959)
- Bug in *`DataFrameGroupBy.tshift()`* failing to raise `ValueError` when a frequency cannot be inferred for the index of a group (GH35937)
- Bug in *`DataFrame.groupby()`* does not always maintain column index name for `any`, `all`, `bfill`, `ffill`, `shift` (GH29764)
- Bug in `DataFrameGroupBy.apply()` raising error with `np.nan` group(s) when `dropna=False` (GH35889)
- Bug in *`Rolling.sum()`* returned wrong values when dtypes where mixed between float and integer and `axis=1` (GH20649, GH35596)
- Bug in *`Rolling.count()`* returned `np.nan` with *`FixedForwardWindowIndexer`* as window, `min_periods=0` and only missing values in the window (GH35579)
- Bug where `pandas.core.window.Rolling` produces incorrect window sizes when using a `PeriodIndex` (GH34225)
- Bug in *`DataFrameGroupBy.ffill()`* and *`DataFrameGroupBy.bfill()`* where a `NaN` group would return filled values instead of `NaN` when `dropna=True` (GH34725)
- Bug in `RollingGroupby.count()` where a `ValueError` was raised when specifying the `closed` parameter (GH35869)
- Bug in `DataFrameGroupBy.rolling()` returning wrong values with partial centered window (GH36040)
- Bug in `DataFrameGroupBy.rolling()` returned wrong values with time aware window containing `NaN`. Raises `ValueError` because windows are not monotonic now (GH34617)
- Bug in `Rolling.__iter__()` where a `ValueError` was not raised when `min_periods` was larger than `window` (GH37156)
- Using *`Rolling.var()`* instead of *`Rolling.std()`* avoids numerical issues for *`Rolling.corr()`* when *`Rolling.var()`* is still within floating point precision while *`Rolling.std()`* is not (GH31286)

- Bug in *DataFrameGroupBy.quantile()* and *Resampler.quantile()* raised TypeError when values were of type Timedelta (GH29485)
- Bug in *Rolling.median()* and *Rolling.quantile()* returned wrong values for *BaseIndexer* subclasses with non-monotonic starting or ending points for windows (GH37153)
- Bug in *DataFrame.groupby()* dropped nan groups from result with dropna=False when grouping over a single column (GH35646, GH35542)
- Bug in DataFrameGroupBy.head(), DataFrameGroupBy.tail(), SeriesGroupBy.head(), and SeriesGroupBy.tail() would raise when used with axis=1 (GH9772)
- Bug in *DataFrameGroupBy.transform()* would raise when used with axis=1 and a transformation kernel (e.g. "shift") (GH36308)
- Bug in *DataFrameGroupBy.resample()* using .agg with sum produced different result than just calling .sum (GH33548)
- Bug in DataFrameGroupBy.apply() dropped values on nan group when returning the same axes with the original frame (GH38227)
- Bug in *DataFrameGroupBy.quantile()* couldn't handle with arraylike q when grouping by columns (GH33795)
- Bug in DataFrameGroupBy.rank() with datetime64tz or period dtype incorrectly casting results to those dtypes instead of returning float64 dtype (GH38187)

Reshaping

- Bug in DataFrame.crosstab() was returning incorrect results on inputs with duplicate row names, duplicate column names or duplicate names between row and column labels (GH22529)
- Bug in *DataFrame.pivot_table()* with aggfunc='count' or aggfunc='sum' returning NaN for missing categories when pivoted on a Categorical. Now returning 0 (GH31422)
- Bug in *concat()* and *DataFrame* constructor where input index names are not preserved in some cases (GH13475)
- Bug in func *crosstab()* when using multiple columns with margins=True and normalize=True (GH35144)
- Bug in *DataFrame.stack()* where an empty DataFrame.stack would raise an error (GH36113). Now returning an empty Series with empty MultiIndex.
- Bug in *Series.unstack()*. Now a Series with single level of Index trying to unstack would raise a ValueError (GH36113)
- Bug in *DataFrame.agg()* with func={'name':<FUNC>} incorrectly raising TypeError when DataFrame.columns==['Name'] (GH36212)
- Bug in *Series.transform()* would give incorrect results or raise when the argument func was a dictionary (GH35811)
- Bug in *DataFrame.pivot()* did not preserve *MultiIndex* level names for columns when rows and columns are both multiindexed (GH36360)
- Bug in *DataFrame.pivot()* modified index argument when columns was passed but values was not (GH37635)
- Bug in *DataFrame.join()* returned a non deterministic level-order for the resulting *MultiIndex* (GH36910)

- Bug in *DataFrame.combine_first()* caused wrong alignment with dtype `string` and one level of `MultiIndex` containing only `NA` (GH37591)
- Fixed regression in *merge()* on merging *DatetimeIndex* with empty DataFrame (GH36895)
- Bug in *DataFrame.apply()* not setting index of return value when `func` return type is `dict` (GH37544)
- Bug in *DataFrame.merge()* and *pandas.merge()* returning inconsistent ordering in result for `how=right` and `how=left` (GH35382)
- Bug in *merge_ordered()* couldn't handle list-like `left_by` or `right_by` (GH35269)
- Bug in *merge_ordered()* returned wrong join result when length of `left_by` or `right_by` equals to the rows of `left` or `right` (GH38166)
- Bug in *merge_ordered()* didn't raise when elements in `left_by` or `right_by` not exist in `left` columns or `right` columns (GH38167)
- Bug in *DataFrame.drop_duplicates()* not validating bool dtype for `ignore_index` keyword (GH38274)

ExtensionArray

- Fixed bug where *DataFrame* column set to scalar extension type via a dict instantiation was considered an object type rather than the extension type (GH35965)
- Fixed bug where `astype()` with equal dtype and `copy=False` would return a new object (GH28488)
- Fixed bug when applying a NumPy ufunc with multiple outputs to an *IntegerArray* returning `None` (GH36913)
- Fixed an inconsistency in *PeriodArray*'s `__init__` signature to those of *DatetimeArray* and *TimedeltaArray* (GH37289)
- Reductions for *BooleanArray*, *Categorical*, *DatetimeArray*, `FloatingArray`, *IntegerArray*, *PeriodArray*, *TimedeltaArray*, and *PandasArray* are now keyword-only methods (GH37541)
- Fixed a bug where a `TypeError` was wrongly raised if a membership check was made on an `ExtensionArray` containing nan-like values (GH37867)

Other

- Bug in *DataFrame.replace()* and *Series.replace()* incorrectly raising an `AssertionError` instead of a `ValueError` when invalid parameter combinations are passed (GH36045)
- Bug in *DataFrame.replace()* and *Series.replace()* with numeric values and string `to_replace` (GH34789)
- Fixed metadata propagation in *Series.abs()* and ufuncs called on Series and DataFrames (GH28283)
- Bug in *DataFrame.replace()* and *Series.replace()* incorrectly casting from `PeriodDtype` to object dtype (GH34871)
- Fixed bug in metadata propagation incorrectly copying DataFrame columns as metadata when the column name overlaps with the metadata name (GH37037)
- Fixed metadata propagation in the *Series.dt*, *Series.str* accessors, *DataFrame.duplicated*, *DataFrame.stack*, *DataFrame.unstack*, *DataFrame.pivot*, *DataFrame.append*, *DataFrame.diff*, *DataFrame.applymap* and *DataFrame.update* methods (GH28283, GH37381)

- Fixed metadata propagation when selecting columns with `DataFrame.__getitem__` (GH28283)
- Bug in *`Index.intersection()`* with non-*`Index`* failing to set the correct name on the returned *`Index`* (GH38111)
- Bug in `RangeIndex.intersection()` failing to set the correct name on the returned *`Index`* in some corner cases (GH38197)
- Bug in *`Index.difference()`* failing to set the correct name on the returned *`Index`* in some corner cases (GH38268)
- Bug in *`Index.union()`* behaving differently depending on whether operand is an *`Index`* or other list-like (GH36384)
- Bug in *`Index.intersection()`* with non-matching numeric dtypes casting to `object` dtype instead of minimal common dtype (GH38122)
- Bug in `IntervalIndex.union()` returning an incorrectly-typed *`Index`* when empty (GH38282)
- Passing an array with 2 or more dimensions to the *`Series`* constructor now raises the more specific `ValueError` rather than a bare `Exception` (GH35744)
- Bug in `dir` where `dir(obj)` wouldn't show attributes defined on the instance for pandas objects (GH37173)
- Bug in *`Index.drop()`* raising `InvalidIndexError` when index has duplicates (GH38051)
- Bug in `RangeIndex.difference()` returning *`Int64Index`* in some cases where it should return *`RangeIndex`* (GH38028)
- Fixed bug in `assert_series_equal()` when comparing a datetime-like array with an equivalent non extension dtype array (GH37609)
- Bug in *`is_bool_dtype()`* would raise when passed a valid string such as `"boolean"` (GH38386)
- Fixed regression in logical operators raising `ValueError` when columns of *`DataFrame`* are a *`CategoricalIndex`* with unused categories (GH38367)

Contributors

A total of 257 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- ivanovmg +
- jbrockmendel
- jeschwar
- jnecus
- joooeey +
- junk +
- krajatcl +
- lacrosse91 +
- leo +
- lpkirwin +
- lrjball
- lucasrodes +
- ma3da +

- mavismonica +
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5.2 Version 1.1

5.2.1 What's new in 1.1.5 (December 07, 2020)

These are the changes in pandas 1.1.5. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in addition of a timedelta-like scalar to a *DatetimeIndex* raising incorrectly (GH37295)
- Fixed regression in *Series.groupby()* raising when the *Index* of the *Series* had a tuple as its name (GH37755)
- Fixed regression in *DataFrame.loc()* and *Series.loc()* for `__setitem__` when one-dimensional tuple was given to select from *MultiIndex* (GH37711)
- Fixed regression in inplace operations on *Series* with `ExtensionDtype` with NumPy dtyped operand (GH37910)
- Fixed regression in metadata propagation for `groupby` iterator (GH37343)
- Fixed regression in *MultiIndex* constructed from a *DatetimeIndex* not retaining frequency (GH35563)
- Fixed regression in *Index* constructor raising a `AttributeError` when passed a `SparseArray` with datetime64 values (GH35843)
- Fixed regression in *DataFrame.unstack()* with columns with integer dtype (GH37115)
- Fixed regression in indexing on a *Series* with `CategoricalDtype` after unpickling (GH37631)
- Fixed regression in *DataFrame.groupby()* aggregation with out-of-bounds datetime objects in an object-dtype column (GH36003)
- Fixed regression in `df.groupby(..).rolling(..)` with the resulting *MultiIndex* when grouping by a label that is in the index (GH37641)
- Fixed regression in *DataFrame.fillna()* not filling `NaN` after other operations such as *DataFrame.pivot()* (GH36495).
- Fixed performance regression in `df.groupby(..).rolling(..)` (GH38038)
- Fixed regression in `MultiIndex.intersection()` returning duplicates when at least one of the indexes had duplicates (GH36915)
- Fixed regression in *GroupBy.first()* and *GroupBy.last()* where `None` was considered a non-NA value (GH38286)

Bug fixes

- Bug in pytables methods in python 3.9 (GH38041)

Other

- Only set `-Werror` as a compiler flag in the CI jobs (GH33315, GH33314)

Contributors

A total of 12 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Andrew Wieteska
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- Janus
- Joris Van den Bossche
- Matthew Roeschke
- MeeseeksMachine
- Pandas Development Team
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- patrick

5.2.2 What's new in 1.1.4 (October 30, 2020)

These are the changes in pandas 1.1.4. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in *read_csv()* raising a `ValueError` when `names` was of type `dict_keys` (GH36928)
- Fixed regression in *read_csv()* with more than 1M rows and specifying a `index_col` argument (GH37094)
- Fixed regression where attempting to mutate a `DateOffset` object would no longer raise an `AttributeError` (GH36940)
- Fixed regression where *DataFrame.agg()* would fail with `TypeError` when passed positional arguments to be passed on to the aggregation function (GH36948).
- Fixed regression in `RollingGroupby` with `sort=False` not being respected (GH36889)
- Fixed regression in *Series.astype()* converting `None` to `"nan"` when casting to string (GH36904)
- Fixed regression in *Series.rank()* method failing for read-only data (GH37290)
- Fixed regression in `RollingGroupby` causing a segmentation fault with Index of dtype object (GH36727)
- Fixed regression in `DataFrame.resample(...).apply(...)()` raised `AttributeError` when input was a *DataFrame* and only a *Series* was evaluated (GH36951)
- Fixed regression in `DataFrame.groupby(..).std()` with nullable integer dtype (GH37415)

- Fixed regression in *PeriodDtype* comparing both equal and unequal to its string representation (GH37265)
- Fixed regression where slicing *DatetimeIndex* raised AssertionError on irregular time series with pd.NaT or on unsorted indices (GH36953 and GH35509)
- Fixed regression in certain offsets (*pd.offsets.Day()* and below) no longer being hashable (GH37267)
- Fixed regression in StataReader which required chunksize to be manually set when using an iterator to read a dataset (GH37280)
- Fixed regression in setitem with *DataFrame.iloc()* which raised error when trying to set a value while filtering with a boolean list (GH36741)
- Fixed regression in setitem with a Series getting aligned before setting the values (GH37427)
- Fixed regression in MultiIndex.is_monotonic_increasing returning wrong results with NaN in at least one of the levels (GH37220)
- Fixed regression in inplace arithmetic operation on a Series not updating the parent DataFrame (GH36373)

Bug fixes

- Bug causing groupby(...).sum() and similar to not preserve metadata (GH29442)
- Bug in *Series.isin()* and *DataFrame.isin()* raising a ValueError when the target was read-only (GH37174)
- Bug in GroupBy.fillna() that introduced a performance regression after 1.0.5 (GH36757)
- Bug in *DataFrame.info()* was raising a KeyError when the DataFrame has integer column names (GH37245)
- Bug in DataFrameGroupby.apply() would drop a *CategoricalIndex* when grouped on (GH35792)

Contributors

A total of 18 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.2.3 What's new in 1.1.3 (October 5, 2020)

These are the changes in pandas 1.1.3. See *Release notes* for a full changelog including other versions of pandas.

Enhancements

Added support for new Python version

pandas 1.1.3 now supports Python 3.9 (GH36296).

Development Changes

- The minimum version of Cython is now the most recent bug-fix version (0.29.21) (GH36296).

Fixed regressions

- Fixed regression in *DataFrame.agg()*, *DataFrame.apply()*, *Series.agg()*, and *Series.apply()* where internal suffix is exposed to the users when no relabelling is applied (GH36189)
- Fixed regression in `IntegerArray` unary plus and minus operations raising a `TypeError` (GH36063)
- Fixed regression when adding a *timedelta_range()* to a *Timestamp* raised a `ValueError` (GH35897)
- Fixed regression in `Series.__getitem__()` incorrectly raising when the input was a tuple (GH35534)
- Fixed regression in `Series.__getitem__()` incorrectly raising when the input was a frozenset (GH35747)
- Fixed regression in modulo of *Index*, *Series* and *DataFrame* using `numexpr` using C not Python semantics (GH36047, GH36526)
- Fixed regression in *read_excel()* with `engine="odf"` caused `UnboundLocalError` in some cases where cells had nested child nodes (GH36122, GH35802)
- Fixed regression in *DataFrame.replace()* inconsistent replace when using a float in the replace method (GH35376)
- Fixed regression in *Series.loc()* on a *Series* with a *MultiIndex* containing *Timestamp* raising `InvalidIndexError` (GH35858)
- Fixed regression in *DataFrame* and *Series* comparisons between numeric arrays and strings (GH35700, GH36377)
- Fixed regression in *DataFrame.apply()* with `raw=True` and user-function returning string (GH35940)
- Fixed regression when setting empty *DataFrame* column to a *Series* in preserving name of index in frame (GH36527)
- Fixed regression in *Period* incorrect value for ordinal over the maximum timestamp (GH36430)

- Fixed regression in *read_table()* raised ValueError when delim_whitespace was set to True (GH35958)
- Fixed regression in *Series.dt.normalize()* when normalizing pre-epoch dates the result was shifted one day (GH36294)

Bug fixes

- Bug in *read_spss()* where passing a pathlib.Path as path would raise a TypeError (GH33666)
- Bug in *Series.str.startswith()* and *Series.str.endswith()* with category dtype not propagating na parameter (GH36241)
- Bug in *Series* constructor where integer overflow would occur for sufficiently large scalar inputs when an index was provided (GH36291)
- Bug in *DataFrame.sort_values()* raising an AttributeError when sorting on a key that casts column to categorical dtype (GH36383)
- Bug in *DataFrame.stack()* raising a ValueError when stacking *MultiIndex* columns based on position when the levels had duplicate names (GH36353)
- Bug in *Series.astype()* showing too much precision when casting from np.float32 to string dtype (GH36451)
- Bug in *Series.isin()* and *DataFrame.isin()* when using NaN and a row length above 1,000,000 (GH22205)
- Bug in *cut()* raising a ValueError when passed a *Series* of labels with ordered=False (GH36603)

Other

- Reverted enhancement added in pandas-1.1.0 where *timedelta_range()* infers a frequency when passed start, stop, and periods (GH32377)

Contributors

A total of 16 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.2.4 What's new in 1.1.2 (September 8, 2020)

These are the changes in pandas 1.1.2. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Regression in `DatetimeIndex.intersection()` incorrectly raising `AssertionError` when intersecting against a list (GH35876)
- Fix regression in updating a column inplace (e.g. using `df['col'].fillna(.., inplace=True)`) (GH35731)
- Fix regression in *`DataFrame.append()`* mixing tz-aware and tz-naive datetime columns (GH35460)
- Performance regression for `RangeIndex.format()` (GH35712)
- Regression where *`MultiIndex.get_loc()`* would return a slice spanning the full index when passed an empty list (GH35878)
- Fix regression in invalid cache after an indexing operation; this can manifest when setting which does not update the data (GH35521)
- Regression in *`DataFrame.replace()`* where a `TypeError` would be raised when attempting to replace elements of type *`Interval`* (GH35931)
- Fix regression in pickle roundtrip of the `closed` attribute of *`IntervalIndex`* (GH35658)
- Fixed regression in `DataFrameGroupBy.agg()` where a `ValueError: buffer source array is read-only` would be raised when the underlying array is read-only (GH36014)
- Fixed regression in `Series.groupby.rolling()` number of levels of *`MultiIndex`* in input was compressed to one (GH36018)
- Fixed regression in `DataFrameGroupBy` on an empty *`DataFrame`* (GH36197)

Bug fixes

- Bug in *`DataFrame.eval()`* with `object` dtype column binary operations (GH35794)
- Bug in *`Series`* constructor raising a `TypeError` when constructing sparse datetime64 dtypes (GH35762)
- Bug in *`DataFrame.apply()`* with `result_type="reduce"` returning with incorrect index (GH35683)
- Bug in *`Series.astype()`* and *`DataFrame.astype()`* not respecting the `errors` argument when set to `"ignore"` for extension dtypes (GH35471)
- Bug in `DateTimeIndex.format()` and `PeriodIndex.format()` with `name=True` setting the first item to `"None"` where it should be `""` (GH35712)
- Bug in `Float64Index.__contains__()` incorrectly raising `TypeError` instead of returning `False` (GH35788)

- Bug in *Series* constructor incorrectly raising a TypeError when passed an ordered set (GH36044)
- Bug in Series.dt.isocalendar() and DatetimeIndex.isocalendar() that returned incorrect year for certain dates (GH36032)
- Bug in *DataFrame* indexing returning an incorrect *Series* in some cases when the series has been altered and a cache not invalidated (GH33675)
- Bug in *DataFrame.corr()* causing subsequent indexing lookups to be incorrect (GH35882)
- Bug in import_optional_dependency() returning incorrect package names in cases where package name is different from import name (GH35948)
- Bug when setting empty *DataFrame* column to a *Series* in preserving name of index in frame (GH31368)

Other

- *factorize()* now supports na_sentinel=None to include NaN in the uniques of the values and remove dropna keyword which was unintentionally exposed to public facing API in 1.1 version from *factorize()* (GH35667)
- *DataFrame.plot()* and *Series.plot()* raise UserWarning about usage of FixedFormatter and FixedLocator (GH35684 and GH35945)

Contributors

A total of 16 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.2.5 What's new in 1.1.1 (August 20, 2020)

These are the changes in pandas 1.1.1. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in `CategoricalIndex.format()` where, when stringified scalars had different lengths, the shorter string would be right-filled with spaces, so it had the same length as the longest string (GH35439)
- Fixed regression in *`Series.truncate()`* when trying to truncate a single-element series (GH35544)
- Fixed regression where *`DataFrame.to_numpy()`* would raise a `RuntimeError` for mixed dtypes when converting to `str` (GH35455)
- Fixed regression where *`read_csv()`* would raise a `ValueError` when `pandas.options.mode.use_inf_as_na` was set to `True` (GH35493)
- Fixed regression where *`pandas.testing.assert_series_equal()`* would raise an error when non-numeric dtypes were passed with `check_exact=True` (GH35446)
- Fixed regression in `.groupby(..).rolling(..)` where column selection was ignored (GH35486)
- Fixed regression where *`DataFrame.interpolate()`* would raise a `TypeError` when the *`DataFrame`* was empty (GH35598)
- Fixed regression in *`DataFrame.shift()`* with `axis=1` and heterogeneous dtypes (GH35488)
- Fixed regression in *`DataFrame.diff()`* with read-only data (GH35559)
- Fixed regression in `.groupby(..).rolling(..)` where a segfault would occur with `center=True` and an odd number of values (GH35552)
- Fixed regression in *`DataFrame.apply()`* where functions that altered the input in-place only operated on a single row (GH35462)
- Fixed regression in *`DataFrame.reset_index()`* would raise a `ValueError` on empty *`DataFrame`* with a *`MultiIndex`* with a `datetime64` dtype level (GH35606, GH35657)
- Fixed regression where *`pandas.merge_asof()`* would raise a `UnboundLocalError` when `left_index`, `right_index` and `tolerance` were set (GH35558)
- Fixed regression in `.groupby(..).rolling(..)` where a custom `BaseIndexer` would be ignored (GH35557)
- Fixed regression in *`DataFrame.replace()`* and *`Series.replace()`* where compiled regular expressions would be ignored during replacement (GH35680)
- Fixed regression in *`aggregate()`* where a list of functions would produce the wrong results if at least one of the functions did not aggregate (GH35490)
- Fixed memory usage issue when instantiating large *`pandas.arrays.StringArray`* (GH35499)

Bug fixes

- Bug in *Styler* whereby cell_ids argument had no effect due to other recent changes (GH35588) (GH35663)
- Bug in *pandas.testing.assert_series_equal()* and *pandas.testing.assert_frame_equal()* where extension dtypes were not ignored when check_dtypes was set to False (GH35715)
- Bug in *to_timedelta()* fails when arg is a *Series* with Int64 dtype containing null values (GH35574)
- Bug in .groupby(..).rolling(..) where passing closed with column selection would raise a ValueError (GH35549)
- Bug in *DataFrame* constructor failing to raise ValueError in some cases when data and index have mismatched lengths (GH33437)

Contributors

A total of 20 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.2.6 What's new in 1.1.0 (July 28, 2020)

These are the changes in pandas 1.1.0. See *Release notes* for a full changelog including other versions of pandas.

Enhancements

KeyErrors raised by loc specify missing labels

Previously, if labels were missing for a `.loc` call, a KeyError was raised stating that this was no longer supported.

Now the error message also includes a list of the missing labels (max 10 items, display width 80 characters). See GH34272.

All dtypes can now be converted to `StringDtype`

Previously, declaring or converting to *`StringDtype`* was in general only possible if the data was already only `str` or nan-like (GH31204). *`StringDtype`* now works in all situations where `astype(str)` or `dtype=str` work:

For example, the below now works:

```
In [1]: ser = pd.Series([1, "abc", np.nan], dtype="string")

In [2]: ser
Out[2]:
0       1
1     abc
2    <NA>
Length: 3, dtype: string

In [3]: ser[0]
Out[3]: '1'

In [4]: pd.Series([1, 2, np.nan], dtype="Int64").astype("string")
Out[4]:
0       1
1       2
2    <NA>
Length: 3, dtype: string
```

Non-monotonic PeriodIndex partial string slicing

`PeriodIndex` now supports partial string slicing for non-monotonic indexes, mirroring *`DatetimeIndex`* behavior (GH31096)

For example:

```
In [5]: dti = pd.date_range("2014-01-01", periods=30, freq="30D")

In [6]: pi = dti.to_period("D")

In [7]: ser_monotonic = pd.Series(np.arange(30), index=pi)

In [8]: shuffler = list(range(0, 30, 2)) + list(range(1, 31, 2))
```

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```
In [9]: ser = ser_monotonic[shuffler]

In [10]: ser
Out[10]:
2014-01-01     0
2014-03-02     2
2014-05-01     4
2014-06-30     6
2014-08-29     8
               ..
2015-09-23    21
2015-11-22    23
2016-01-21    25
2016-03-21    27
2016-05-20    29
Freq: D, Length: 30, dtype: int64
```

```
In [11]: ser["2014"]
Out[11]:
2014-01-01     0
2014-03-02     2
2014-05-01     4
2014-06-30     6
2014-08-29     8
2014-10-28    10
2014-12-27    12
2014-01-31     1
2014-04-01     3
2014-05-31     5
2014-07-30     7
2014-09-28     9
2014-11-27    11
Freq: D, Length: 13, dtype: int64

In [12]: ser.loc["May 2015"]
Out[12]:
2015-05-26    17
Freq: D, Length: 1, dtype: int64
```

Comparing two `DataFrame` or two `Series` and summarizing the differences

We've added *`DataFrame.compare()`* and *`Series.compare()`* for comparing two `DataFrame` or two `Series` (GH30429)

```
In [13]: df = pd.DataFrame(
   ....:     {
   ....:         "col1": ["a", "a", "b", "b", "a"],
   ....:         "col2": [1.0, 2.0, 3.0, np.nan, 5.0],
   ....:         "col3": [1.0, 2.0, 3.0, 4.0, 5.0]
   ....:     },
   ....:     columns=["col1", "col2", "col3"],
   ....: )
   ....:
```

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```
In [14]: df
Out[14]:
  col1  col2  col3
0    a   1.0   1.0
1    a   2.0   2.0
2    b   3.0   3.0
3    b   NaN   4.0
4    a   5.0   5.0

[5 rows x 3 columns]
```

```
In [15]: df2 = df.copy()

In [16]: df2.loc[0, 'col1'] = 'c'

In [17]: df2.loc[2, 'col3'] = 4.0

In [18]: df2
Out[18]:
  col1  col2  col3
0    c   1.0   1.0
1    a   2.0   2.0
2    b   3.0   4.0
3    b   NaN   4.0
4    a   5.0   5.0

[5 rows x 3 columns]
```

```
In [19]: df.compare(df2)
Out[19]:
  col1       col3
  self other self other
0    a     c  NaN   NaN
2  NaN   NaN  3.0   4.0

[2 rows x 4 columns]
```

See *User Guide* for more details.

Allow NA in groupby key

With *groupby* , we've added a `dropna` keyword to *`DataFrame.groupby()`* and *`Series.groupby()`* in order to allow `NA` values in group keys. Users can define `dropna` to `False` if they want to include `NA` values in groupby keys. The default is set to `True` for `dropna` to keep backwards compatibility (GH3729)

```
In [20]: df_list = [[1, 2, 3], [1, None, 4], [2, 1, 3], [1, 2, 2]]

In [21]: df_dropna = pd.DataFrame(df_list, columns=["a", "b", "c"])

In [22]: df_dropna
Out[22]:
   a    b  c
0  1  2.0  3
1  1  NaN  4
```

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```
2  2  1.0  3
3  1  2.0  2

[4 rows x 3 columns]
```

```
# Default ``dropna`` is set to True, which will exclude NaNs in keys
In [23]: df_dropna.groupby(by=["b"], dropna=True).sum()
Out[23]:
     a  c
b
1.0  2  3
2.0  2  5

[2 rows x 2 columns]

# In order to allow NaN in keys, set ``dropna`` to False
In [24]: df_dropna.groupby(by=["b"], dropna=False).sum()
Out[24]:
     a  c
b
1.0  2  3
2.0  2  5
NaN  1  4

[3 rows x 2 columns]
```

The default setting of `dropna` argument is `True` which means `NA` are not included in group keys.

Sorting with keys

We've added a `key` argument to the *`DataFrame`* and *`Series`* sorting methods, including *`DataFrame.sort_values()`*, *`DataFrame.sort_index()`*, *`Series.sort_values()`*, and *`Series.sort_index()`*. The `key` can be any callable function which is applied column-by-column to each column used for sorting, before sorting is performed (GH27237). See *sort_values with keys* and *sort_index with keys* for more information.

```
In [25]: s = pd.Series(['C', 'a', 'B'])

In [26]: s
Out[26]:
0    C
1    a
2    B
Length: 3, dtype: object
```

```
In [27]: s.sort_values()
Out[27]:
2    B
0    C
1    a
Length: 3, dtype: object
```

Note how this is sorted with capital letters first. If we apply the *`Series.str.lower()`* method, we get

```
In [28]: s.sort_values(key=lambda x: x.str.lower())
Out[28]:
1    a
2    B
0    C
Length: 3, dtype: object
```

When applied to a `DataFrame`, they key is applied per-column to all columns or a subset if `by` is specified, e.g.

```
In [29]: df = pd.DataFrame({'a': ['C', 'C', 'a', 'a', 'B', 'B'],
   ....:                    'b': [1, 2, 3, 4, 5, 6]})
   ....:

In [30]: df
Out[30]:
   a  b
0  C  1
1  C  2
2  a  3
3  a  4
4  B  5
5  B  6

[6 rows x 2 columns]
```

```
In [31]: df.sort_values(by=['a'], key=lambda col: col.str.lower())
Out[31]:
   a  b
2  a  3
3  a  4
4  B  5
5  B  6
0  C  1
1  C  2

[6 rows x 2 columns]
```

For more details, see examples and documentation in *DataFrame.sort_values()*, *Series.sort_values()*, and *sort_index()*.

Fold argument support in Timestamp constructor

`Timestamp`: now supports the keyword-only fold argument according to PEP 495 similar to parent `datetime.datetime` class. It supports both accepting fold as an initialization argument and inferring fold from other constructor arguments (GH25057, GH31338). Support is limited to `dateutil` timezones as `pytz` doesn't support fold.

For example:

```
In [32]: ts = pd.Timestamp("2019-10-27 01:30:00+00:00")

In [33]: ts.fold
Out[33]: 0
```

```
In [34]: ts = pd.Timestamp(year=2019, month=10, day=27, hour=1, minute=30,
   ....:                   tz="dateutil/Europe/London", fold=1)
```

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```
   ....:

In [35]: ts
Out[35]: Timestamp('2019-10-27 01:30:00+0000', tz='dateutil//usr/share/zoneinfo/
↪Europe/London')
```

For more on working with fold, see *Fold subsection* in the user guide.

Parsing timezone-aware format with different timezones in to_datetime

to_datetime() now supports parsing formats containing timezone names (`%Z`) and UTC offsets (`%z`) from different timezones then converting them to UTC by setting `utc=True`. This would return a *DatetimeIndex* with timezone at UTC as opposed to an *Index* with `object` dtype if `utc=True` is not set (GH32792).

For example:

```
In [36]: tz_strs = ["2010-01-01 12:00:00 +0100", "2010-01-01 12:00:00 -0100",
   ....:            "2010-01-01 12:00:00 +0300", "2010-01-01 12:00:00 +0400"]
   ....:

In [37]: pd.to_datetime(tz_strs, format='%Y-%m-%d %H:%M:%S %z', utc=True)
Out[37]:
DatetimeIndex(['2010-01-01 11:00:00+00:00', '2010-01-01 13:00:00+00:00',
               '2010-01-01 09:00:00+00:00', '2010-01-01 08:00:00+00:00'],
              dtype='datetime64[ns, UTC]', freq=None)

In [38]: pd.to_datetime(tz_strs, format='%Y-%m-%d %H:%M:%S %z')
Out[38]:
Index([2010-01-01 12:00:00+01:00, 2010-01-01 12:00:00-01:00,
       2010-01-01 12:00:00+03:00, 2010-01-01 12:00:00+04:00],
      dtype='object')
```

Grouper and resample now supports the arguments origin and offset

Grouper and *DataFrame.resample()* now supports the arguments `origin` and `offset`. It let the user control the timestamp on which to adjust the grouping. (GH31809)

The bins of the grouping are adjusted based on the beginning of the day of the time series starting point. This works well with frequencies that are multiples of a day (like `30D`) or that divides a day (like `90s` or `1min`). But it can create inconsistencies with some frequencies that do not meet this criteria. To change this behavior you can now specify a fixed timestamp with the argument `origin`.

Two arguments are now deprecated (more information in the documentation of *DataFrame.resample()*):

- `base` should be replaced by `offset`.
- `loffset` should be replaced by directly adding an offset to the index *DataFrame* after being resampled.

Small example of the use of `origin`:

```
In [39]: start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'

In [40]: middle = '2000-10-02 00:00:00'

In [41]: rng = pd.date_range(start, end, freq='7min')
```

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```
In [42]: ts = pd.Series(np.arange(len(rng)) * 3, index=rng)

In [43]: ts
Out[43]:
2000-10-01 23:30:00     0
2000-10-01 23:37:00     3
2000-10-01 23:44:00     6
2000-10-01 23:51:00     9
2000-10-01 23:58:00    12
2000-10-02 00:05:00    15
2000-10-02 00:12:00    18
2000-10-02 00:19:00    21
2000-10-02 00:26:00    24
Freq: 7T, Length: 9, dtype: int64
```

Resample with the default behavior `'start_day'` (origin is `2000-10-01 00:00:00`):

```
In [44]: ts.resample('17min').sum()
Out[44]:
2000-10-01 23:14:00     0
2000-10-01 23:31:00     9
2000-10-01 23:48:00    21
2000-10-02 00:05:00    54
2000-10-02 00:22:00    24
Freq: 17T, Length: 5, dtype: int64

In [45]: ts.resample('17min', origin='start_day').sum()
Out[45]:
2000-10-01 23:14:00     0
2000-10-01 23:31:00     9
2000-10-01 23:48:00    21
2000-10-02 00:05:00    54
2000-10-02 00:22:00    24
Freq: 17T, Length: 5, dtype: int64
```

Resample using a fixed origin:

```
In [46]: ts.resample('17min', origin='epoch').sum()
Out[46]:
2000-10-01 23:18:00     0
2000-10-01 23:35:00    18
2000-10-01 23:52:00    27
2000-10-02 00:09:00    39
2000-10-02 00:26:00    24
Freq: 17T, Length: 5, dtype: int64

In [47]: ts.resample('17min', origin='2000-01-01').sum()
Out[47]:
2000-10-01 23:24:00     3
2000-10-01 23:41:00    15
2000-10-01 23:58:00    45
2000-10-02 00:15:00    45
Freq: 17T, Length: 4, dtype: int64
```

If needed you can adjust the bins with the argument `offset` (a *Timedelta*) that would be added to the default `origin`.

For a full example, see: *Use origin or offset to adjust the start of the bins*.

fsspec now used for filesystem handling

For reading and writing to filesystems other than local and reading from HTTP(S), the optional dependency `fsspec` will be used to dispatch operations (GH33452). This will give unchanged functionality for S3 and GCS storage, which were already supported, but also add support for several other storage implementations such as Azure Datalake and Blob, SSH, FTP, dropbox and github. For docs and capabilities, see the fsspec docs.

The existing capability to interface with S3 and GCS will be unaffected by this change, as `fsspec` will still bring in the same packages as before.

Other enhancements

- Compatibility with matplotlib 3.3.0 (GH34850)
- `IntegerArray.astype()` now supports `datetime64` dtype (GH32538)
- `IntegerArray` now implements the `sum` operation (GH33172)
- Added *pandas.errors.InvalidIndexError* (GH34570).
- Added *DataFrame.value_counts()* (GH5377)
- Added a *pandas.api.indexers.FixedForwardWindowIndexer()* class to support forward-looking windows during `rolling` operations.
- Added a *pandas.api.indexers.VariableOffsetWindowIndexer()* class to support `rolling` operations with non-fixed offsets (GH34994)
- *describe()* now includes a `datetime_is_numeric` keyword to control how datetime columns are summarized (GH30164, GH34798)
- *Styler* may now render CSS more efficiently where multiple cells have the same styling (GH30876)
- *highlight_null()* now accepts `subset` argument (GH31345)
- When writing directly to a sqlite connection *DataFrame.to_sql()* now supports the `multi` method (GH29921)
- `pandas.errors.OptionError` is now exposed in `pandas.errors` (GH27553)
- Added `api.extensions.ExtensionArray.argmax()` and `api.extensions.ExtensionArray.argmin()` (GH24382)
- *timedelta_range()* will now infer a frequency when passed `start`, `stop`, and `periods` (GH32377)
- Positional slicing on a *IntervalIndex* now supports slices with `step > 1` (GH31658)
- *Series.str* now has a `fullmatch` method that matches a regular expression against the entire string in each row of the *Series*, similar to `re.fullmatch` (GH32806).
- *DataFrame.sample()* will now also allow array-like and BitGenerator objects to be passed to `random_state` as seeds (GH32503)
- *Index.union()* will now raise `RuntimeWarning` for *MultiIndex* objects if the object inside are unsortable. Pass `sort=False` to suppress this warning (GH33015)
- Added `Series.dt.isocalendar()` and `DatetimeIndex.isocalendar()` that returns a *DataFrame* with year, week, and day calculated according to the ISO 8601 calendar (GH33206, GH34392).

- The *DataFrame.to_feather()* method now supports additional keyword arguments (e.g. to set the compression) that are added in pyarrow 0.17 (GH33422).
- The *cut()* will now accept parameter `ordered` with default `ordered=True`. If `ordered=False` and no labels are provided, an error will be raised (GH33141)
- *DataFrame.to_csv()*, *DataFrame.to_pickle()*, and *DataFrame.to_json()* now support passing a dict of compression arguments when using the `gzip` and `bz2` protocols. This can be used to set a custom compression level, e.g., `df.to_csv(path, compression={'method': 'gzip', 'compresslevel': 1}` (GH33196)
- *melt()* has gained an `ignore_index` (default `True`) argument that, if set to `False`, prevents the method from dropping the index (GH17440).
- *Series.update()* now accepts objects that can be coerced to a *Series*, such as `dict` and `list`, mirroring the behavior of *DataFrame.update()* (GH33215)
- *transform()* and *aggregate()* have gained `engine` and `engine_kwargs` arguments that support executing functions with `Numba` (GH32854, GH33388)
- *interpolate()* now supports SciPy interpolation method `scipy.interpolate.CubicSpline` as method `cubicspline` (GH33670)
- `DataFrameGroupBy` and `SeriesGroupBy` now implement the `sample` method for doing random sampling within groups (GH31775)
- *DataFrame.to_numpy()* now supports the `na_value` keyword to control the NA sentinel in the output array (GH33820)
- Added `api.extension.ExtensionArray.equals` to the extension array interface, similar to *Series.equals()* (GH27081)
- The minimum supported dta version has increased to 105 in *read_stata()* and `StataReader` (GH26667).
- *to_stata()* supports compression using the `compression` keyword argument. Compression can either be inferred or explicitly set using a string or a dictionary containing both the method and any additional arguments that are passed to the compression library. Compression was also added to the low-level Stata-file writers `StataWriter`, `StataWriter117`, and `StataWriterUTF8` (GH26599).
- *HDFStore.put()* now accepts a `track_times` parameter. This parameter is passed to the `create_table` method of `PyTables` (GH32682).
- *Series.plot()* and *DataFrame.plot()* now accepts `xlabel` and `ylabel` parameters to present labels on x and y axis (GH9093).
- Made `pandas.core.window.rolling.Rolling` and `pandas.core.window.expanding.Expanding` iterableGH11704)
- Made `option_context` a `contextlib.ContextDecorator`, which allows it to be used as a decorator over an entire function (GH34253).
- *DataFrame.to_csv()* and *Series.to_csv()* now accept an `errors` argument (GH22610)
- `transform()` now allows `func` to be `pad`, `backfill` and `cumcount` (GH31269).
- *read_json()* now accepts an `nrows` parameter. (GH33916).
- *DataFrame.hist()*, *Series.hist()*, *core.groupby.DataFrameGroupBy.hist()*, and *core.groupby.SeriesGroupBy.hist()* have gained the `legend` argument. Set to True to show a legend in the histogram. (GH6279)
- *concat()* and *append()* now preserve extension dtypes, for example combining a nullable integer column with a numpy integer column will no longer result in object dtype but preserve the integer dtype (GH33607, GH34339, GH34095).

- *read_gbq()* now allows to disable progress bar (GH33360).
- *read_gbq()* now supports the `max_results` kwarg from `pandas-gbq` (GH34639).
- *DataFrame.cov()* and *Series.cov()* now support a new parameter `ddof` to support delta degrees of freedom as in the corresponding numpy methods (GH34611).
- *DataFrame.to_html()* and *DataFrame.to_string()*'s `col_space` parameter now accepts a list or dict to change only some specific columns' width (GH28917).
- *DataFrame.to_excel()* can now also write OpenOffice spreadsheet (.ods) files (GH27222)
- *explode()* now accepts `ignore_index` to reset the index, similar to `pd.concat()` or *DataFrame.sort_values()* (GH34932).
- *DataFrame.to_markdown()* and *Series.to_markdown()* now accept `index` argument as an alias for tabulate's `showindex` (GH32667)
- *read_csv()* now accepts string values like "0", "0.0", "1", "1.0" as convertible to the nullable Boolean dtype (GH34859)
- `pandas.core.window.ExponentialMovingWindow` now supports a `times` argument that allows `mean` to be calculated with observations spaced by the timestamps in `times` (GH34839)
- *DataFrame.agg()* and *Series.agg()* now accept named aggregation for renaming the output columns/indexes. (GH26513)
- `compute.use_numba` now exists as a configuration option that utilizes the numba engine when available (GH33966, GH35374)
- *Series.plot()* now supports asymmetric error bars. Previously, if *Series.plot()* received a "2xN" array with error values for `yerr` and/or `xerr`, the left/lower values (first row) were mirrored, while the right/upper values (second row) were ignored. Now, the first row represents the left/lower error values and the second row the right/upper error values. (GH9536)

Notable bug fixes

These are bug fixes that might have notable behavior changes.

`MultiIndex.get_indexer` interprets `method` argument correctly

This restores the behavior of *MultiIndex.get_indexer()* with `method='backfill'` or `method='pad'` to the behavior before pandas 0.23.0. In particular, MultiIndexes are treated as a list of tuples and padding or backfilling is done with respect to the ordering of these lists of tuples (GH29896).

As an example of this, given:

```
In [48]: df = pd.DataFrame({
   ....:     'a': [0, 0, 0, 0],
   ....:     'b': [0, 2, 3, 4],
   ....:     'c': ['A', 'B', 'C', 'D'],
   ....: }).set_index(['a', 'b'])
   ....:

In [49]: mi_2 = pd.MultiIndex.from_product([[0], [-1, 0, 1, 3, 4, 5]])
```

The differences in reindexing `df` with `mi_2` and using `method='backfill'` can be seen here:

pandas >= 0.23, < 1.1.0:

```
In [1]: df.reindex(mi_2, method='backfill')
Out[1]:
      c
0 -1  A
   0  A
   1  D
   3  A
   4  A
   5  C
```

pandas <0.23, >= 1.1.0

```
In [50]: df.reindex(mi_2, method='backfill')
Out[50]:
        c
0 -1    A
   0    A
   1    B
   3    C
   4    D
   5  NaN

[6 rows x 1 columns]
```

And the differences in reindexing `df` with `mi_2` and using `method='pad'` can be seen here:

pandas >= 0.23, < 1.1.0

```
In [1]: df.reindex(mi_2, method='pad')
Out[1]:
        c
0 -1  NaN
   0  NaN
   1    D
   3  NaN
   4    A
   5    C
```

pandas < 0.23, >= 1.1.0

```
In [51]: df.reindex(mi_2, method='pad')
Out[51]:
        c
0 -1  NaN
   0    A
   1    A
   3    C
   4    D
   5    D

[6 rows x 1 columns]
```

Failed label-based lookups always raise KeyError

Label lookups `series[key]`, `series.loc[key]` and `frame.loc[key]` used to raise either `KeyError` or `TypeError` depending on the type of key and type of *Index*. These now consistently raise `KeyError` (GH31867)

```
In [52]: ser1 = pd.Series(range(3), index=[0, 1, 2])

In [53]: ser2 = pd.Series(range(3), index=pd.date_range("2020-02-01", periods=3))
```

Previous behavior:

```
In [3]: ser1[1.5]
...
TypeError: cannot do label indexing on Int64Index with these indexers [1.5] of type␣
↪float

In [4] ser1["foo"]
...
KeyError: 'foo'

In [5]: ser1.loc[1.5]
...
TypeError: cannot do label indexing on Int64Index with these indexers [1.5] of type␣
↪float

In [6]: ser1.loc["foo"]
...
KeyError: 'foo'

In [7]: ser2.loc[1]
...
TypeError: cannot do label indexing on DatetimeIndex with these indexers [1] of type␣
↪int

In [8]: ser2.loc[pd.Timestamp(0)]
...
KeyError: Timestamp('1970-01-01 00:00:00')
```

New behavior:

```
In [3]: ser1[1.5]
...
KeyError: 1.5

In [4] ser1["foo"]
...
KeyError: 'foo'

In [5]: ser1.loc[1.5]
...
KeyError: 1.5

In [6]: ser1.loc["foo"]
...
KeyError: 'foo'

In [7]: ser2.loc[1]
```

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```
...
KeyError: 1

In [8]: ser2.loc[pd.Timestamp(0)]
...
KeyError: Timestamp('1970-01-01 00:00:00')
```

Similarly, *DataFrame.at()* and *Series.at()* will raise a `TypeError` instead of a `ValueError` if an incompatible key is passed, and `KeyError` if a missing key is passed, matching the behavior of `.loc[]` (GH31722)

Failed Integer Lookups on MultiIndex Raise KeyError

Indexing with integers with a *MultiIndex* that has an integer-dtype first level incorrectly failed to raise `KeyError` when one or more of those integer keys is not present in the first level of the index (GH33539)

```
In [54]: idx = pd.Index(range(4))

In [55]: dti = pd.date_range("2000-01-03", periods=3)

In [56]: mi = pd.MultiIndex.from_product([idx, dti])

In [57]: ser = pd.Series(range(len(mi)), index=mi)
```

Previous behavior:

```
In [5]: ser[[5]]
Out[5]: Series([], dtype: int64)
```

New behavior:

```
In [5]: ser[[5]]
...
KeyError: '[5] not in index'
```

`DataFrame.merge()` preserves right frame's row order

DataFrame.merge() now preserves the right frame's row order when executing a right merge (GH27453)

```
In [58]: left_df = pd.DataFrame({'animal': ['dog', 'pig'],
   ....:                         'max_speed': [40, 11]})
   ....:

In [59]: right_df = pd.DataFrame({'animal': ['quetzal', 'pig'],
   ....:                          'max_speed': [80, 11]})
   ....:

In [60]: left_df
Out[60]:
  animal  max_speed
0    dog         40
1    pig         11

[2 rows x 2 columns]
```

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```
In [61]: right_df
Out[61]:
    animal  max_speed
0  quetzal         80
1      pig         11

[2 rows x 2 columns]
```

Previous behavior:

```
>>> left_df.merge(right_df, on=['animal', 'max_speed'], how="right")
    animal  max_speed
0      pig         11
1  quetzal         80
```

New behavior:

```
In [62]: left_df.merge(right_df, on=['animal', 'max_speed'], how="right")
Out[62]:
    animal  max_speed
0  quetzal         80
1      pig         11

[2 rows x 2 columns]
```

Assignment to multiple columns of a DataFrame when some columns do not exist

Assignment to multiple columns of a *DataFrame* when some of the columns do not exist would previously assign the values to the last column. Now, new columns will be constructed with the right values. (GH13658)

```
In [63]: df = pd.DataFrame({'a': [0, 1, 2], 'b': [3, 4, 5]})

In [64]: df
Out[64]:
   a  b
0  0  3
1  1  4
2  2  5

[3 rows x 2 columns]
```

Previous behavior:

```
In [3]: df[['a', 'c']] = 1
In [4]: df
Out[4]:
   a  b
0  1  1
1  1  1
2  1  1
```

New behavior:

```
In [65]: df[['a', 'c']] = 1

In [66]: df
Out[66]:
   a  b  c
0  1  3  1
1  1  4  1
2  1  5  1

[3 rows x 3 columns]
```

Consistency across groupby reductions

Using *DataFrame.groupby()* with `as_index=True` and the aggregation `nunique` would include the grouping column(s) in the columns of the result. Now the grouping column(s) only appear in the index, consistent with other reductions. (GH32579)

```
In [67]: df = pd.DataFrame({"a": ["x", "x", "y", "y"], "b": [1, 1, 2, 3]})

In [68]: df
Out[68]:
   a  b
0  x  1
1  x  1
2  y  2
3  y  3

[4 rows x 2 columns]
```

Previous behavior:

```
In [3]: df.groupby("a", as_index=True).nunique()
Out[4]:
   a  b
a
x  1  1
y  1  2
```

New behavior:

```
In [69]: df.groupby("a", as_index=True).nunique()
Out[69]:
   b
a
x  1
y  2

[2 rows x 1 columns]
```

Using *DataFrame.groupby()* with `as_index=False` and the function `idxmax`, `idxmin`, `mad`, `nunique`, `sem`, `skew`, or `std` would modify the grouping column. Now the grouping column remains unchanged, consistent with other reductions. (GH21090, GH10355)

Previous behavior:

```
In [3]: df.groupby("a", as_index=False).nunique()
Out[4]:
   a  b
0  1  1
1  1  2
```

New behavior:

```
In [70]: df.groupby("a", as_index=False).nunique()
Out[70]:
   a  b
0  x  1
1  y  2

[2 rows x 2 columns]
```

The method *size()* would previously ignore `as_index=False`. Now the grouping columns are returned as columns, making the result a *DataFrame* instead of a *Series*. (GH32599)

Previous behavior:

```
In [3]: df.groupby("a", as_index=False).size()
Out[4]:
a
x    2
y    2
dtype: int64
```

New behavior:

```
In [71]: df.groupby("a", as_index=False).size()
Out[71]:
   a  size
0  x     2
1  y     2

[2 rows x 2 columns]
```

`agg()` lost results with `as_index=False` when relabeling columns

Previously `agg()` lost the result columns, when the `as_index` option was set to `False` and the result columns were relabeled. In this case the result values were replaced with the previous index (GH32240).

```
In [72]: df = pd.DataFrame({"key": ["x", "y", "z", "x", "y", "z"],
   ....:                    "val": [1.0, 0.8, 2.0, 3.0, 3.6, 0.75]})
   ....:

In [73]: df
Out[73]:
  key   val
0   x  1.00
1   y  0.80
2   z  2.00
3   x  3.00
4   y  3.60
5   z  0.75
```

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```
[6 rows x 2 columns]
```

Previous behavior:

```
In [2]: grouped = df.groupby("key", as_index=False)
In [3]: result = grouped.agg(min_val=pd.NamedAgg(column="val", aggfunc="min"))
In [4]: result
Out[4]:
     min_val
 0   x
 1   y
 2   z
```

New behavior:

```
In [74]: grouped = df.groupby("key", as_index=False)

In [75]: result = grouped.agg(min_val=pd.NamedAgg(column="val", aggfunc="min"))

In [76]: result
Out[76]:
  key  min_val
0   x     1.00
1   y     0.80
2   z     0.75

[3 rows x 2 columns]
```

apply and applymap on `DataFrame` evaluates first row/column only once

```
In [77]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 6]})

In [78]: def func(row):
   ....:     print(row)
   ....:     return row
   ....:
```

Previous behavior:

```
In [4]: df.apply(func, axis=1)
a    1
b    3
Name: 0, dtype: int64
a    1
b    3
Name: 0, dtype: int64
a    2
b    6
Name: 1, dtype: int64
Out[4]:
   a  b
0  1  3
1  2  6
```

New behavior:

```
In [79]: df.apply(func, axis=1)
a    1
b    3
Name: 0, Length: 2, dtype: int64
a    2
b    6
Name: 1, Length: 2, dtype: int64
Out[79]:
   a  b
0  1  3
1  2  6

[2 rows x 2 columns]
```

Backwards incompatible API changes

Added `check_freq` argument to `testing.assert_frame_equal` and `testing.assert_series_equal`

The `check_freq` argument was added to *`testing.assert_frame_equal()`* and *`testing.assert_series_equal()`* in pandas 1.1.0 and defaults to `True`. *`testing.assert_frame_equal()`* and *`testing.assert_series_equal()`* now raise `AssertionError` if the indexes do not have the same frequency. Before pandas 1.1.0, the index frequency was not checked.

Increased minimum versions for dependencies

Some minimum supported versions of dependencies were updated (GH33718, GH29766, GH29723, pytables >= 3.4.3). If installed, we now require:

Package	Minimum Version	Required	Changed
numpy	1.15.4	X	X
pytz	2015.4	X	
python-dateutil	2.7.3	X	X
bottleneck	1.2.1		
numexpr	2.6.2		
pytest (dev)	4.0.2		

For optional libraries the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

Package	Minimum Version	Changed
beautifulsoup4	4.6.0	
fastparquet	0.3.2	
fsspec	0.7.4	
gcsfs	0.6.0	X
lxml	3.8.0	
matplotlib	2.2.2	
numba	0.46.0	
openpyxl	2.5.7	
pyarrow	0.13.0	
pymysql	0.7.1	
pytables	3.4.3	X
s3fs	0.4.0	X
scipy	1.2.0	X
sqlalchemy	1.1.4	
xarray	0.8.2	
xlrd	1.1.0	
xlsxwriter	0.9.8	
xlwt	1.2.0	
pandas-gbq	1.2.0	X

See *Dependencies* and *Optional dependencies* for more.

Development changes

- The minimum version of Cython is now the most recent bug-fix version (0.29.16) (GH33334).

Deprecations

- Lookups on a *Series* with a single-item list containing a slice (e.g. `ser[[slice(0, 4)]]`) are deprecated and will raise in a future version. Either convert the list to a tuple, or pass the slice directly instead (GH31333)
- *DataFrame.mean()* and *DataFrame.median()* with `numeric_only=None` will include `datetime64` and `datetime64tz` columns in a future version (GH29941)
- Setting values with `.loc` using a positional slice is deprecated and will raise in a future version. Use `.loc` with labels or `.iloc` with positions instead (GH31840)
- *DataFrame.to_dict()* has deprecated accepting short names for `orient` and will raise in a future version (GH32515)
- `Categorical.to_dense()` is deprecated and will be removed in a future version, use `np.asarray(cat)` instead (GH32639)
- The `fastpath` keyword in the `SingleBlockManager` constructor is deprecated and will be removed in a future version (GH33092)
- Providing `suffixes` as a `set` in *pandas.merge()* is deprecated. Provide a tuple instead (GH33740, GH34741).
- Indexing a *Series* with a multi-dimensional indexer like `[:, None]` to return an `ndarray` now raises a `FutureWarning`. Convert to a NumPy array before indexing instead (GH27837)
- *Index.is_mixed()* is deprecated and will be removed in a future version, check `index.inferred_type` directly instead (GH32922)

- Passing any arguments but the first one to *read_html()* as positional arguments is deprecated. All other arguments should be given as keyword arguments (GH27573).
- Passing any arguments but path_or_buf (the first one) to *read_json()* as positional arguments is deprecated. All other arguments should be given as keyword arguments (GH27573).
- Passing any arguments but the first two to *read_excel()* as positional arguments is deprecated. All other arguments should be given as keyword arguments (GH27573).
- *pandas.api.types.is_categorical()* is deprecated and will be removed in a future version; use *pandas.api.types.is_categorical_dtype()* instead (GH33385)
- *Index.get_value()* is deprecated and will be removed in a future version (GH19728)
- *Series.dt.week()* and *Series.dt.weekofyear()* are deprecated and will be removed in a future version, use Series.dt.isocalendar().week() instead (GH33595)
- *DatetimeIndex.week()* and DatetimeIndex.weekofyear are deprecated and will be removed in a future version, use DatetimeIndex.isocalendar().week instead (GH33595)
- DatetimeArray.week() and DatetimeArray.weekofyear are deprecated and will be removed in a future version, use DatetimeArray.isocalendar().week instead (GH33595)
- DateOffset.__call__() is deprecated and will be removed in a future version, use offset + other instead (GH34171)
- *apply_index()* is deprecated and will be removed in a future version. Use offset + other instead (GH34580)
- *DataFrame.tshift()* and *Series.tshift()* are deprecated and will be removed in a future version, use *DataFrame.shift()* and *Series.shift()* instead (GH11631)
- Indexing an *Index* object with a float key is deprecated, and will raise an IndexError in the future. You can manually convert to an integer key instead (GH34191).
- The squeeze keyword in *groupby()* is deprecated and will be removed in a future version (GH32380)
- The tz keyword in *Period.to_timestamp()* is deprecated and will be removed in a future version; use per.to_timestamp(...).tz_localize(tz) instead (GH34522)
- *DatetimeIndex.to_perioddelta()* is deprecated and will be removed in a future version. Use index - index.to_period(freq).to_timestamp() instead (GH34853)
- *DataFrame.melt()* accepting a value_name that already exists is deprecated, and will be removed in a future version (GH34731)
- The center keyword in the *DataFrame.expanding()* function is deprecated and will be removed in a future version (GH20647)

Performance improvements

- Performance improvement in *Timedelta* constructor (GH30543)
- Performance improvement in *Timestamp* constructor (GH30543)
- Performance improvement in flex arithmetic ops between *DataFrame* and *Series* with axis=0 (GH31296)
- Performance improvement in arithmetic ops between *DataFrame* and *Series* with axis=1 (GH33600)
- The internal index method _shallow_copy() now copies cached attributes over to the new index, avoiding creating these again on the new index. This can speed up many operations that depend on creating copies of existing indexes (GH28584, GH32640, GH32669)

- Significant performance improvement when creating a *DataFrame* with sparse values from scipy.sparse matrices using the *DataFrame.sparse.from_spmatrix()* constructor (GH32821, GH32825, GH32826, GH32856, GH32858).
- Performance improvement for groupby methods first() and last() (GH34178)
- Performance improvement in *factorize()* for nullable (integer and Boolean) dtypes (GH33064).
- Performance improvement when constructing *Categorical* objects (GH33921)
- Fixed performance regression in *pandas.qcut()* and *pandas.cut()* (GH33921)
- Performance improvement in reductions (sum, prod, min, max) for nullable (integer and Boolean) dtypes (GH30982, GH33261, GH33442).
- Performance improvement in arithmetic operations between two *DataFrame* objects (GH32779)
- Performance improvement in pandas.core.groupby.RollingGroupby (GH34052)
- Performance improvement in arithmetic operations (sub, add, mul, div) for *MultiIndex* (GH34297)
- Performance improvement in DataFrame[bool_indexer] when bool_indexer is a list (GH33924)
- Significant performance improvement of *io.formats.style.Styler.render()* with styles added with various ways such as *io.formats.style.Styler.apply()*, *io.formats.style.Styler.applymap()* or *io.formats.style.Styler.bar()* (GH19917)

Bug fixes

Categorical

- Passing an invalid fill_value to Categorical.take() raises a ValueError instead of TypeError (GH33660)
- Combining a *Categorical* with integer categories and which contains missing values with a float dtype column in operations such as *concat()* or *append()* will now result in a float column instead of an object dtype column (GH33607)
- Bug where *merge()* was unable to join on non-unique categorical indices (GH28189)
- Bug when passing categorical data to *Index* constructor along with dtype=object incorrectly returning a *CategoricalIndex* instead of object-dtype *Index* (GH32167)
- Bug where *Categorical* comparison operator __ne__ would incorrectly evaluate to False when either element was missing (GH32276)
- Categorical.fillna() now accepts *Categorical* other argument (GH32420)
- Repr of *Categorical* was not distinguishing between int and str (GH33676)

Datetimelike

- Passing an integer dtype other than int64 to np.array(period_index, dtype=...) will now raise TypeError instead of incorrectly using int64 (GH32255)
- *Series.to_timestamp()* now raises a TypeError if the axis is not a *PeriodIndex*. Previously an AttributeError was raised (GH33327)
- *Series.to_period()* now raises a TypeError if the axis is not a *DatetimeIndex*. Previously an AttributeError was raised (GH33327)

- *Period* no longer accepts tuples for the freq argument (GH34658)
- Bug in *Timestamp* where constructing a *Timestamp* from ambiguous epoch time and calling constructor again changed the *Timestamp.value()* property (GH24329)
- DatetimeArray.searchsorted(), TimedeltaArray.searchsorted(), PeriodArray.searchsorted() not recognizing non-pandas scalars and incorrectly raising ValueError instead of TypeError (GH30950)
- Bug in *Timestamp* where constructing *Timestamp* with dateutil timezone less than 128 nanoseconds before daylight saving time switch from winter to summer would result in nonexistent time (GH31043)
- Bug in *Period.to_timestamp()*, *Period.start_time()* with microsecond frequency returning a timestamp one nanosecond earlier than the correct time (GH31475)
- *Timestamp* raised a confusing error message when year, month or day is missing (GH31200)
- Bug in *DatetimeIndex* constructor incorrectly accepting bool-dtype inputs (GH32668)
- Bug in DatetimeIndex.searchsorted() not accepting a list or *Series* as its argument (GH32762)
- Bug where *PeriodIndex()* raised when passed a *Series* of strings (GH26109)
- Bug in *Timestamp* arithmetic when adding or subtracting an np.ndarray with timedelta64 dtype (GH33296)
- Bug in *DatetimeIndex.to_period()* not inferring the frequency when called with no arguments (GH33358)
- Bug in *DatetimeIndex.tz_localize()* incorrectly retaining freq in some cases where the original freq is no longer valid (GH30511)
- Bug in DatetimeIndex.intersection() losing freq and timezone in some cases (GH33604)
- Bug in DatetimeIndex.get_indexer() where incorrect output would be returned for mixed datetime-like targets (GH33741)
- Bug in *DatetimeIndex* addition and subtraction with some types of DateOffset objects incorrectly retaining an invalid freq attribute (GH33779)
- Bug in *DatetimeIndex* where setting the freq attribute on an index could silently change the freq attribute on another index viewing the same data (GH33552)
- *DataFrame.min()* and *DataFrame.max()* were not returning consistent results with *Series.min()* and *Series.max()* when called on objects initialized with empty pd.to_datetime()
- Bug in DatetimeIndex.intersection() and TimedeltaIndex.intersection() with results not having the correct name attribute (GH33904)
- Bug in DatetimeArray.__setitem__(), TimedeltaArray.__setitem__(), PeriodArray.__setitem__() incorrectly allowing values with int64 dtype to be silently cast (GH33717)
- Bug in subtracting *TimedeltaIndex* from *Period* incorrectly raising TypeError in some cases where it should succeed and IncompatibleFrequency in some cases where it should raise TypeError (GH33883)
- Bug in constructing a *Series* or *Index* from a read-only NumPy array with non-ns resolution which converted to object dtype instead of coercing to datetime64[ns] dtype when within the timestamp bounds (GH34843).
- The freq keyword in *Period*, *date_range()*, *period_range()*, pd.tseries.frequencies.to_offset() no longer allows tuples, pass as string instead (GH34703)
- Bug in *DataFrame.append()* when appending a *Series* containing a scalar tz-aware *Timestamp* to an empty *DataFrame* resulted in an object column instead of datetime64[ns, tz] dtype (GH35038)

- `OutOfBoundsDatetime` issues an improved error message when timestamp is out of implementation bounds. (GH32967)
- Bug in `AbstractHolidayCalendar.holidays()` when no rules were defined (GH31415)
- Bug in `Tick` comparisons raising `TypeError` when comparing against timedelta-like objects (GH34088)
- Bug in `Tick` multiplication raising `TypeError` when multiplying by a float (GH34486)

Timedelta

- Bug in constructing a *`Timedelta`* with a high precision integer that would round the *`Timedelta`* components (GH31354)
- Bug in dividing `np.nan` or `None` by *`Timedelta`* incorrectly returning `NaT` (GH31869)
- *`Timedelta`* now understands `µs` as an identifier for microsecond (GH32899)
- *`Timedelta`* string representation now includes nanoseconds, when nanoseconds are non-zero (GH9309)
- Bug in comparing a *`Timedelta`* object against an `np.ndarray` with `timedelta64` dtype incorrectly viewing all entries as unequal (GH33441)
- Bug in *`timedelta_range()`* that produced an extra point on a edge case (GH30353, GH33498)
- Bug in *`DataFrame.resample()`* that produced an extra point on a edge case (GH30353, GH13022, GH33498)
- Bug in *`DataFrame.resample()`* that ignored the `loffset` argument when dealing with timedelta (GH7687, GH33498)
- Bug in *`Timedelta`* and *`pandas.to_timedelta()`* that ignored the `unit` argument for string input (GH12136)

Timezones

- Bug in *`to_datetime()`* with `infer_datetime_format=True` where timezone names (e.g. `UTC`) would not be parsed correctly (GH33133)

Numeric

- Bug in *`DataFrame.floordiv()`* with `axis=0` not treating division-by-zero like *`Series.floordiv()`* (GH31271)
- Bug in *`to_numeric()`* with string argument `"uint64"` and `errors="coerce"` silently fails (GH32394)
- Bug in *`to_numeric()`* with `downcast="unsigned"` fails for empty data (GH32493)
- Bug in *`DataFrame.mean()`* with `numeric_only=False` and either `datetime64` dtype or `PeriodDtype` column incorrectly raising `TypeError` (GH32426)
- Bug in *`DataFrame.count()`* with `level="foo"` and index level `"foo"` containing NaNs causes segmentation fault (GH21824)
- Bug in *`DataFrame.diff()`* with `axis=1` returning incorrect results with mixed dtypes (GH32995)
- Bug in *`DataFrame.corr()`* and *`DataFrame.cov()`* raising when handling nullable integer columns with `pandas.NA` (GH33803)

- Bug in arithmetic operations between *DataFrame* objects with non-overlapping columns with duplicate labels causing an infinite loop (GH35194)
- Bug in *DataFrame* and *Series* addition and subtraction between object-dtype objects and `datetime64` dtype objects (GH33824)
- Bug in *Index.difference()* giving incorrect results when comparing a *Float64Index* and object *Index* (GH35217)
- Bug in *DataFrame* reductions (e.g. `df.min()`, `df.max()`) with `ExtensionArray` dtypes (GH34520, GH32651)
- *Series.interpolate()* and *DataFrame.interpolate()* now raise a ValueError if `limit_direction` is `'forward'` or `'both'` and `method` is `'backfill'` or `'bfill'` or `limit_direction` is `'backward'` or `'both'` and `method` is `'pad'` or `'ffill'` (GH34746)

Conversion

- Bug in *Series* construction from NumPy array with big-endian `datetime64` dtype (GH29684)
- Bug in *Timedelta* construction with large nanoseconds keyword value (GH32402)
- Bug in *DataFrame* construction where sets would be duplicated rather than raising (GH32582)
- The *DataFrame* constructor no longer accepts a list of *DataFrame* objects. Because of changes to NumPy, *DataFrame* objects are now consistently treated as 2D objects, so a list of *DataFrame* objects is considered 3D, and no longer acceptable for the *DataFrame* constructor (GH32289).
- Bug in *DataFrame* when initiating a frame with lists and assign `columns` with nested list for `MultiIndex` (GH32173)
- Improved error message for invalid construction of list when creating a new index (GH35190)

Strings

- Bug in the *astype()* method when converting "string" dtype data to nullable integer dtype (GH32450).
- Fixed issue where taking `min` or `max` of a `StringArray` or `Series` with `StringDtype` type would raise. (GH31746)
- Bug in *Series.str.cat()* returning `NaN` output when other had *Index* type (GH33425)
- `pandas.api.dtypes.is_string_dtype()` no longer incorrectly identifies categorical series as string.

Interval

- Bug in `IntervalArray` incorrectly allowing the underlying data to be changed when setting values (GH32782)

Indexing

- *DataFrame.xs()* now raises a TypeError if a level keyword is supplied and the axis is not a *MultiIndex*. Previously an AttributeError was raised (GH33610)
- Bug in slicing on a *DatetimeIndex* with a partial-timestamp dropping high-resolution indices near the end of a year, quarter, or month (GH31064)
- Bug in PeriodIndex.get_loc() treating higher-resolution strings differently from PeriodIndex.get_value() (GH31172)
- Bug in *Series.at()* and *DataFrame.at()* not matching .loc behavior when looking up an integer in a *Float64Index* (GH31329)
- Bug in PeriodIndex.is_monotonic() incorrectly returning True when containing leading NaT entries (GH31437)
- Bug in DatetimeIndex.get_loc() raising KeyError with converted-integer key instead of the user-passed key (GH31425)
- Bug in *Series.xs()* incorrectly returning Timestamp instead of datetime64 in some object-dtype cases (GH31630)
- Bug in *DataFrame.iat()* incorrectly returning Timestamp instead of datetime in some object-dtype cases (GH32809)
- Bug in *DataFrame.at()* when either columns or index is non-unique (GH33041)
- Bug in *Series.loc()* and *DataFrame.loc()* when indexing with an integer key on a object-dtype *Index* that is not all-integers (GH31905)
- Bug in DataFrame.iloc.__setitem__() on a *DataFrame* with duplicate columns incorrectly setting values for all matching columns (GH15686, GH22036)
- Bug in *DataFrame.loc()* and *Series.loc()* with a *DatetimeIndex*, *TimedeltaIndex*, or *PeriodIndex* incorrectly allowing lookups of non-matching datetime-like dtypes (GH32650)
- Bug in Series.__getitem__() indexing with non-standard scalars, e.g. np.dtype (GH32684)
- Bug in *Index* constructor where an unhelpful error message was raised for NumPy scalars (GH33017)
- Bug in *DataFrame.lookup()* incorrectly raising an AttributeError when frame.index or frame.columns is not unique; this will now raise a ValueError with a helpful error message (GH33041)
- Bug in *Interval* where a *Timedelta* could not be added or subtracted from a *Timestamp* interval (GH32023)
- Bug in *DataFrame.copy()* not invalidating _item_cache after copy caused post-copy value updates to not be reflected (GH31784)
- Fixed regression in *DataFrame.loc()* and *Series.loc()* throwing an error when a datetime64[ns, tz] value is provided (GH32395)
- Bug in Series.__getitem__() with an integer key and a *MultiIndex* with leading integer level failing to raise KeyError if the key is not present in the first level (GH33355)
- Bug in *DataFrame.iloc()* when slicing a single column *DataFrame* with ExtensionDtype (e.g. df.iloc[:, :1]) returning an invalid result (GH32957)
- Bug in DatetimeIndex.insert() and TimedeltaIndex.insert() causing index freq to be lost when setting an element into an empty *Series* (GH33573)
- Bug in Series.__setitem__() with an *IntervalIndex* and a list-like key of integers (GH33473)

- Bug in `Series.__getitem__()` allowing missing labels with `np.ndarray`, *Index*, *Series* indexers but not `list`, these now all raise `KeyError` (GH33646)
- Bug in *DataFrame.truncate()* and *Series.truncate()* where index was assumed to be monotone increasing (GH33756)
- Indexing with a list of strings representing datetimes failed on *DatetimeIndex* or *PeriodIndex* (GH11278)
- Bug in *Series.at()* when used with a *MultiIndex* would raise an exception on valid inputs (GH26989)
- Bug in *DataFrame.loc()* with dictionary of values changes columns with dtype of `int` to `float` (GH34573)
- Bug in *Series.loc()* when used with a *MultiIndex* would raise an `IndexingError` when accessing a `None` value (GH34318)
- Bug in *DataFrame.reset_index()* and *Series.reset_index()* would not preserve data types on an empty *DataFrame* or *Series* with a *MultiIndex* (GH19602)
- Bug in *Series* and *DataFrame* indexing with a `time` key on a *DatetimeIndex* with `NaT` entries (GH35114)

Missing

- Calling `fillna()` on an empty *Series* now correctly returns a shallow copied object. The behaviour is now consistent with *Index*, *DataFrame* and a non-empty *Series* (GH32543).
- Bug in *Series.replace()* when argument `to_replace` is of type dict/list and is used on a *Series* containing `<NA>` was raising a `TypeError`. The method now handles this by ignoring `<NA>` values when doing the comparison for the replacement (GH32621)
- Bug in *any()* and *all()* incorrectly returning `<NA>` for all `False` or all `True` values using the nulllable Boolean dtype and with `skipna=False` (GH33253)
- Clarified documentation on interpolate with `method=akima`. The `der` parameter must be scalar or `None` (GH33426)
- *DataFrame.interpolate()* uses the correct axis convention now. Previously interpolating along columns lead to interpolation along indices and vice versa. Furthermore interpolating with methods `pad`, `ffill`, `bfill` and `backfill` are identical to using these methods with *DataFrame.fillna()* (GH12918, GH29146)
- Bug in *DataFrame.interpolate()* when called on a *DataFrame* with column names of string type was throwing a ValueError. The method is now independent of the type of the column names (GH33956)
- Passing `NA` into a format string using format specs will now work. For example `"{:.1f}".format(pd.NA)` would previously raise a `ValueError`, but will now return the string `"<NA>"` (GH34740)
- Bug in *Series.map()* not raising on invalid `na_action` (GH32815)

MultiIndex

- `DataFrame.swaplevels()` now raises a `TypeError` if the axis is not a *`MultiIndex`*. Previously an `AttributeError` was raised (GH31126)
- Bug in `Dataframe.loc()` when used with a *`MultiIndex`*. The returned values were not in the same order as the given inputs (GH22797)

```
In [80]: df = pd.DataFrame(np.arange(4),
   ....:                   index=[["a", "a", "b", "b"], [1, 2, 1, 2]])
   ....:

# Rows are now ordered as the requested keys
In [81]: df.loc[(['b', 'a'], [2, 1]), :]
Out[81]:
     0
b 2  3
  1  2
a 2  1
  1  0

[4 rows x 1 columns]
```

- Bug in `MultiIndex.intersection()` was not guaranteed to preserve order when `sort=False`. (GH31325)
- Bug in *`DataFrame.truncate()`* was dropping *`MultiIndex`* names. (GH34564)

```
In [82]: left = pd.MultiIndex.from_arrays([["b", "a"], [2, 1]])

In [83]: right = pd.MultiIndex.from_arrays([["a", "b", "c"], [1, 2, 3]])

# Common elements are now guaranteed to be ordered by the left side
In [84]: left.intersection(right, sort=False)
Out[84]:
MultiIndex([('b', 2),
            ('a', 1)],
           )
```

- Bug when joining two *`MultiIndex`* without specifying level with different columns. Return-indexers parameter was ignored. (GH34074)

IO

- Passing a `set` as `names` argument to *`pandas.read_csv()`*, *`pandas.read_table()`*, or *`pandas.read_fwf()`* will raise `ValueError: Names should be an ordered collection.` (GH34946)
- Bug in print-out when `display.precision` is zero. (GH20359)
- Bug in *`read_json()`* where integer overflow was occurring when json contains big number strings. (GH30320)
- *`read_csv()`* will now raise a `ValueError` when the arguments `header` and `prefix` both are not `None`. (GH27394)
- Bug in *`DataFrame.to_json()`* was raising `NotFoundError` when `path_or_buf` was an S3 URI (GH28375)

- Bug in *DataFrame.to_parquet()* overwriting pyarrow's default for `coerce_timestamps`; following pyarrow's default allows writing nanosecond timestamps with `version="2.0"` (GH31652).
- Bug in *read_csv()* was raising `TypeError` when `sep=None` was used in combination with `comment` keyword (GH31396)
- Bug in `HDFStore` that caused it to set to `int64` the dtype of a `datetime64` column when reading a *DataFrame* in Python 3 from fixed format written in Python 2 (GH31750)
- *read_sas()* now handles dates and datetimes larger than *Timestamp.max* returning them as `datetime.datetime` objects (GH20927)
- Bug in *DataFrame.to_json()* where `Timedelta` objects would not be serialized correctly with `date_format="iso"` (GH28256)
- *read_csv()* will raise a `ValueError` when the column names passed in `parse_dates` are missing in the `Dataframe` (GH31251)
- Bug in *read_excel()* where a UTF-8 string with a high surrogate would cause a segmentation violation (GH23809)
- Bug in *read_csv()* was causing a file descriptor leak on an empty file (GH31488)
- Bug in *read_csv()* was causing a segfault when there were blank lines between the header and data rows (GH28071)
- Bug in *read_csv()* was raising a misleading exception on a permissions issue (GH23784)
- Bug in *read_csv()* was raising an `IndexError` when `header=None` and two extra data columns
- Bug in *read_sas()* was raising an `AttributeError` when reading files from Google Cloud Storage (GH33069)
- Bug in *DataFrame.to_sql()* where an `AttributeError` was raised when saving an out of bounds date (GH26761)
- Bug in *read_excel()* did not correctly handle multiple embedded spaces in OpenDocument text cells. (GH32207)
- Bug in *read_json()* was raising `TypeError` when reading a `list` of Booleans into a *Series*. (GH31464)
- Bug in `pandas.io.json.json_normalize()` where location specified by `record_path` doesn't point to an array. (GH26284)
- *pandas.read_hdf()* has a more explicit error message when loading an unsupported HDF file (GH9539)
- Bug in `read_feather()` was raising an `ArrowIOError` when reading an s3 or http file path (GH29055)
- Bug in *to_excel()* could not handle the column name `render` and was raising an `KeyError` (GH34331)
- Bug in `execute()` was raising a `ProgrammingError` for some DB-API drivers when the SQL statement contained the `%` character and no parameters were present (GH34211)
- Bug in `StataReader()` which resulted in categorical variables with different dtypes when reading data using an iterator. (GH31544)
- *HDFStore.keys()* has now an optional `include` parameter that allows the retrieval of all native HDF5 table names (GH29916)
- `TypeError` exceptions raised by *read_csv()* and *read_table()* were showing as `parser_f` when an unexpected keyword argument was passed (GH25648)
- Bug in *read_excel()* for ODS files removes 0.0 values (GH27222)

- Bug in `ujson.encode()` was raising an `OverflowError` with numbers larger than `sys.maxsize` (GH34395)
- Bug in `HDFStore.append_to_multiple()` was raising a `ValueError` when the `min_itemsize` parameter is set (GH11238)
- Bug in `create_table()` now raises an error when `column` argument was not specified in `data_columns` on input (GH28156)
- *`read_json()`* now could read line-delimited json file from a file url while `lines` and `chunksize` are set.
- Bug in *`DataFrame.to_sql()`* when reading DataFrames with `-np.inf` entries with MySQL now has a more explicit `ValueError` (GH34431)
- Bug where capitalised files extensions were not decompressed by read_* functions (GH35164)
- Bug in *`read_excel()`* that was raising a `TypeError` when `header=None` and `index_col` is given as a `list` (GH31783)
- Bug in *`read_excel()`* where datetime values are used in the header in a *`MultiIndex`* (GH34748)
- *`read_excel()`* no longer takes `**kwds` arguments. This means that passing in the keyword argument `chunksize` now raises a `TypeError` (previously raised a `NotImplementedError`), while passing in the keyword argument `encoding` now raises a `TypeError` (GH34464)
- Bug in *`DataFrame.to_records()`* was incorrectly losing timezone information in timezone-aware `datetime64` columns (GH32535)

Plotting

- *`DataFrame.plot()`* for line/bar now accepts color by dictionary (GH8193).
- Bug in *`DataFrame.plot.hist()`* where weights are not working for multiple columns (GH33173)
- Bug in *`DataFrame.boxplot()`* and `DataFrame.plot.boxplot()` lost color attributes of `medianprops`, `whiskerprops`, `capprops` and `boxprops` (GH30346)
- Bug in *`DataFrame.hist()`* where the order of `column` argument was ignored (GH29235)
- Bug in *`DataFrame.plot.scatter()`* that when adding multiple plots with different `cmap`, colorbars always use the first `cmap` (GH33389)
- Bug in *`DataFrame.plot.scatter()`* was adding a colorbar to the plot even if the argument `c` was assigned to a column containing color names (GH34316)
- Bug in *`pandas.plotting.bootstrap_plot()`* was causing cluttered axes and overlapping labels (GH34905)
- Bug in *`DataFrame.plot.scatter()`* caused an error when plotting variable marker sizes (GH32904)

GroupBy/resample/rolling

- Using a *`pandas.api.indexers.BaseIndexer`* with `count`, `min`, `max`, `median`, `skew`, `cov`, `corr` will now return correct results for any monotonic *`pandas.api.indexers.BaseIndexer`* descendant (GH32865)
- `DataFrameGroupby.mean()` and `SeriesGroupby.mean()` (and similarly for `median()`, `std()` and `var()`) now raise a `TypeError` if a non-accepted keyword argument is passed into it. Previously an `UnsupportedFunctionCall` was raised (`AssertionError` if `min_count` passed into `median()`) (GH31485)

- Bug in `GroupBy.apply()` raises `ValueError` when the `by` axis is not sorted, has duplicates, and the applied `func` does not mutate passed in objects (GH30667)
- Bug in `DataFrameGroupBy.transform()` produces an incorrect result with transformation functions (GH30918)
- Bug in `Groupby.transform()` was returning the wrong result when grouping by multiple keys of which some were categorical and others not (GH32494)
- Bug in `GroupBy.count()` causes segmentation fault when grouped-by columns contain NaNs (GH32841)
- Bug in *`DataFrame.groupby()`* and *`Series.groupby()`* produces inconsistent type when aggregating Boolean *`Series`* (GH32894)
- Bug in `DataFrameGroupBy.sum()` and `SeriesGroupBy.sum()` where a large negative number would be returned when the number of non-null values was below `min_count` for nullable integer dtypes (GH32861)
- Bug in `SeriesGroupBy.quantile()` was raising on nullable integers (GH33136)
- Bug in *`DataFrame.resample()`* where an `AmbiguousTimeError` would be raised when the resulting timezone aware *`DatetimeIndex`* had a DST transition at midnight (GH25758)
- Bug in *`DataFrame.groupby()`* where a `ValueError` would be raised when grouping by a categorical column with read-only categories and `sort=False` (GH33410)
- Bug in `GroupBy.agg()`, `GroupBy.transform()`, and `GroupBy.resample()` where subclasses are not preserved (GH28330)
- Bug in `SeriesGroupBy.agg()` where any column name was accepted in the named aggregation of `SeriesGroupBy` previously. The behaviour now allows only `str` and callables else would raise `TypeError`. (GH34422)
- Bug in *`DataFrame.groupby()`* lost the name of the *`Index`* when one of the `agg` keys referenced an empty list (GH32580)
- Bug in `Rolling.apply()` where `center=True` was ignored when `engine='numba'` was specified (GH34784)
- Bug in `DataFrame.ewm.cov()` was throwing `AssertionError` for *`MultiIndex`* inputs (GH34440)
- Bug in *`core.groupby.DataFrameGroupBy.quantile()`* raised `TypeError` for non-numeric types rather than dropping the columns (GH27892)
- Bug in *`core.groupby.DataFrameGroupBy.transform()`* when `func='nunique'` and columns are of type `datetime64`, the result would also be of type `datetime64` instead of `int64` (GH35109)
- Bug in *`DataFrame.groupby()`* raising an `AttributeError` when selecting a column and aggregating with `as_index=False` (GH35246).
- Bug in `DataFrameGroupBy.first()` and `DataFrameGroupBy.last()` that would raise an unnecessary `ValueError` when grouping on multiple `Categoricals` (GH34951)

Reshaping

- Bug effecting all numeric and Boolean reduction methods not returning subclassed data type. (GH25596)
- Bug in *DataFrame.pivot_table()* when only MultiIndexed columns is set (GH17038)
- Bug in *DataFrame.unstack()* and *Series.unstack()* can take tuple names in MultiIndexed data (GH19966)
- Bug in *DataFrame.pivot_table()* when margin is True and only column is defined (GH31016)
- Fixed incorrect error message in *DataFrame.pivot()* when columns is set to None. (GH30924)
- Bug in *crosstab()* when inputs are two *Series* and have tuple names, the output will keep a dummy *MultiIndex* as columns. (GH18321)
- *DataFrame.pivot()* can now take lists for index and columns arguments (GH21425)
- Bug in *concat()* where the resulting indices are not copied when copy=True (GH29879)
- Bug in SeriesGroupBy.aggregate() was resulting in aggregations being overwritten when they shared the same name (GH30880)
- Bug where *Index.astype()* would lose the name attribute when converting from Float64Index to Int64Index, or when casting to an ExtensionArray dtype (GH32013)
- *Series.append()* will now raise a TypeError when passed a *DataFrame* or a sequence containing *DataFrame* (GH31413)
- *DataFrame.replace()* and *Series.replace()* will raise a TypeError if to_replace is not an expected type. Previously the replace would fail silently (GH18634)
- Bug on inplace operation of a *Series* that was adding a column to the *DataFrame* from where it was originally dropped from (using inplace=True) (GH30484)
- Bug in *DataFrame.apply()* where callback was called with *Series* parameter even though raw=True requested. (GH32423)
- Bug in *DataFrame.pivot_table()* losing timezone information when creating a *MultiIndex* level from a column with timezone-aware dtype (GH32558)
- Bug in *concat()* where when passing a non-dict mapping as objs would raise a TypeError (GH32863)
- *DataFrame.agg()* now provides more descriptive SpecificationError message when attempting to aggregate a non-existent column (GH32755)
- Bug in *DataFrame.unstack()* when *MultiIndex* columns and *MultiIndex* rows were used (GH32624, GH24729 and GH28306)
- Appending a dictionary to a *DataFrame* without passing ignore_index=True will raise TypeError: Can only append a dict if ignore_index=True instead of TypeError: Can only append a :class:`Series` if ignore_index=True or if the :class:`Series` has a name (GH30871)
- Bug in *DataFrame.corrwith()*, *DataFrame.memory_usage()*, *DataFrame.dot()*, *DataFrame.idxmin()*, *DataFrame.idxmax()*, *DataFrame.duplicated()*, *DataFrame.isin()*, *DataFrame.count()*, *Series.explode()*, *Series.asof()* and *DataFrame.asof()* not returning subclassed types. (GH31331)
- Bug in *concat()* was not allowing for concatenation of *DataFrame* and *Series* with duplicate keys (GH33654)
- Bug in *cut()* raised an error when the argument labels contains duplicates (GH33141)
- Ensure only named functions can be used in *eval()* (GH32460)

- Bug in `Dataframe.aggregate()` and *Series.aggregate()* was causing a recursive loop in some cases (GH34224)
- Fixed bug in *melt()* where melting *MultiIndex* columns with `col_level > 0` would raise a `KeyError` on `id_vars` (GH34129)
- Bug in *Series.where()* with an empty *Series* and empty `cond` having non-bool dtype (GH34592)
- Fixed regression where *DataFrame.apply()* would raise `ValueError` for elements with `S` dtype (GH34529)

Sparse

- Creating a `SparseArray` from timezone-aware dtype will issue a warning before dropping timezone information, instead of doing so silently (GH32501)
- Bug in `arrays.SparseArray.from_spmatrix()` wrongly read scipy sparse matrix (GH31991)
- Bug in *Series.sum()* with `SparseArray` raised a `TypeError` (GH25777)
- Bug where *DataFrame* containing an all-sparse `SparseArray` filled with `NaN` when indexed by a list-like (GH27781, GH29563)
- The repr of *SparseDtype* now includes the repr of its `fill_value` attribute. Previously it used `fill_value`'s string representation (GH34352)
- Bug where empty *DataFrame* could not be cast to *SparseDtype* (GH33113)
- Bug in *arrays.SparseArray()* was returning the incorrect type when indexing a sparse dataframe with an iterable (GH34526, GH34540)

ExtensionArray

- Fixed bug where *Series.value_counts()* would raise on empty input of `Int64` dtype (GH33317)
- Fixed bug in *concat()* when concatenating *DataFrame* objects with non-overlapping columns resulting in object-dtype columns rather than preserving the extension dtype (GH27692, GH33027)
- Fixed bug where `StringArray.isna()` would return `False` for NA values when `pandas.options.mode.use_inf_as_na` was set to `True` (GH33655)
- Fixed bug in *Series* construction with EA dtype and index but no data or scalar data fails (GH26469)
- Fixed bug that caused `Series.__repr__()` to crash for extension types whose elements are multidimensional arrays (GH33770).
- Fixed bug where *Series.update()* would raise a `ValueError` for `ExtensionArray` dtypes with missing values (GH33980)
- Fixed bug where `StringArray.memory_usage()` was not implemented (GH33963)
- Fixed bug where `DataFrameGroupBy()` would ignore the `min_count` argument for aggregations on nullable Boolean dtypes (GH34051)
- Fixed bug where the constructor of *DataFrame* with `dtype='string'` would fail (GH27953, GH33623)
- Bug where *DataFrame* column set to scalar extension type was considered an object type rather than the extension type (GH34832)
- Fixed bug in `IntegerArray.astype()` to correctly copy the mask as well (GH34931).

Other

- Set operations on an object-dtype *Index* now always return object-dtype results (GH31401)
- Fixed *pandas.testing.assert_series_equal()* to correctly raise if the `left` argument is a different subclass with `check_series_type=True` (GH32670).
- Getting a missing attribute in a *DataFrame.query()* or *DataFrame.eval()* string raises the correct `AttributeError` (GH32408)
- Fixed bug in *pandas.testing.assert_series_equal()* where dtypes were checked for `Interval` and `ExtensionArray` operands when `check_dtype` was `False` (GH32747)
- Bug in `DataFrame.__dir__()` caused a segfault when using unicode surrogates in a column name (GH25509)
- Bug in *DataFrame.equals()* and *Series.equals()* in allowing subclasses to be equal (GH34402).

Contributors

A total of 368 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- brock +
- chris-b1
- cleconte987 +
- dan1261 +
- david-cortes +
- davidwales +
- dequadras +
- dhuettenmoser +
- dilex42 +
- elmonsomiat +

- epizzigoni +
- fjetter
- gabrielvf1 +
- gdex1 +
- gfyoung
- guru kiran +
- h-vishal
- iamshwin
- jamin-aws-ospo +
- jbrockmendel
- jfcorbett +
- jnecus +
- kernc
- kota matsuoka +
- kylekeppler +
- leandermaben +
- link2xt +
- manoj_koneni +
- marydmit +
- masterpiga +
- maxime.song +
- mglasder +
- moaraccounts +
- mproszewska
- neilkg
- nrebena
- ossdev07 +
- paihu
- pan Jacek +
- partev +
- patrick +
- pedrooa +
- pizzathief +
- proost
- pvanhauw +
- rbenes

- rebecca-palmer
- rhshadrach +
- rjfs +
- s-scherrer +
- sage +
- sagungrp +
- salem3358 +
- saloni30 +
- smartswdeveloper +
- smartvinnetou +
- themien +
- timhunderwood +
- tolhassianipar +
- tonywu1999
- tsvikas
- tv3141
- venkateshdatta1993 +
- vivikelapoutre +
- willbowditch +
- willpeppo +
- za +
- zaki-indra +

5.3 Version 1.0

5.3.1 What's new in 1.0.5 (June 17, 2020)

These are the changes in pandas 1.0.5. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fix regression in `read_parquet()` when reading from file-like objects (GH34467).
- Fix regression in reading from public S3 buckets (GH34626).

Note this disables the ability to read Parquet files from directories on S3 again (GH26388, GH34632), which was added in the 1.0.4 release, but is now targeted for pandas 1.1.0.

- Fixed regression in `replace()` raising an `AssertionError` when replacing values in an extension dtype with values of a different dtype (GH34530)

Bug fixes

- Fixed building from source with Python 3.8 fetching the wrong version of NumPy (GH34666)

Contributors

A total of 8 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Joris Van den Bossche
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- Tom Augspurger
- William Ayd
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5.3.2 What's new in 1.0.4 (May 28, 2020)

These are the changes in pandas 1.0.4. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fix regression where *Series.isna()* and *DataFrame.isna()* would raise for categorical dtype when `pandas.options.mode.use_inf_as_na` was set to `True` (GH33594)
- Fix regression in `GroupBy.first()` and `GroupBy.last()` where None is not preserved in object dtype (GH32800)
- Fix regression in DataFrame reductions using `numeric_only=True` and ExtensionArrays (GH33256).
- Fix performance regression in `memory_usage(deep=True)` for object dtype (GH33012)
- Fix regression where `Categorical.replace()` would replace with `NaN` whenever the new value and replacement value were equal (GH33288)
- Fix regression where an ordered *Categorical* containing only `NaN` values would raise rather than returning `NaN` when taking the minimum or maximum (GH33450)
- Fix regression in `DataFrameGroupBy.agg()` with dictionary input losing `ExtensionArray` dtypes (GH32194)
- Fix to preserve the ability to index with the "nearest" method with xarray's CFTimeIndex, an *Index* subclass (pydata/xarray#3751, GH32905).
- Fix regression in *DataFrame.describe()* raising `TypeError: unhashable type: 'dict'` (GH32409)
- Fix regression in *DataFrame.replace()* casts columns to `object` dtype if items in `to_replace` not in values (GH32988)
- Fix regression in *Series.groupby()* would raise `ValueError` when grouping by *PeriodIndex* level (GH34010)

- Fix regression in `GroupBy.rolling.apply()` ignores args and kwargs parameters (GH33433)
- Fix regression in error message with `np.min` or `np.max` on unordered *`Categorical`* (GH33115)
- Fix regression in *`DataFrame.loc()`* and *`Series.loc()`* throwing an error when a `datetime64[ns, tz]` value is provided (GH32395)

Bug fixes

- Bug in `SeriesGroupBy.first()`, `SeriesGroupBy.last()`, `SeriesGroupBy.min()`, and `SeriesGroupBy.max()` returning floats when applied to nullable Booleans (GH33071)
- Bug in `Rolling.min()` and `Rolling.max()`: Growing memory usage after multiple calls when using a fixed window (GH30726)
- Bug in *`to_parquet()`* was not raising `PermissionError` when writing to a private s3 bucket with invalid creds. (GH27679)
- Bug in *`to_csv()`* was silently failing when writing to an invalid s3 bucket. (GH32486)
- Bug in *`read_parquet()`* was raising a `FileNotFoundError` when passed an s3 directory path. (GH26388)
- Bug in *`to_parquet()`* was throwing an `AttributeError` when writing a partitioned parquet file to s3 (GH27596)
- Bug in `GroupBy.quantile()` causes the quantiles to be shifted when the `by` axis contains `NaN` (GH33200, GH33569)

Contributors

A total of 18 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- JDkuba +
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- Kaiqi Dong
- Mabel Villalba
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- alimcmaster1
- h-vishal +
- jbrockmendel
- mproszewska +

- neilkg +
- rebecca-palmer +

5.3.3 What's new in 1.0.3 (March 17, 2020)

These are the changes in pandas 1.0.3. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in `resample.agg` when the underlying data is non-writeable (GH31710)
- Fixed regression in *`DataFrame`* exponentiation with reindexing (GH32685)

Bug fixes

Contributors

A total of 5 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- MeeseeksMachine
- Pandas Development Team
- Tom Augspurger
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5.3.4 What's new in 1.0.2 (March 12, 2020)

These are the changes in pandas 1.0.2. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

Groupby

- Fixed regression in *`groupby(..).agg()`* which was failing on frames with *`MultiIndex`* columns and a custom function (GH31777)
- Fixed regression in `groupby(..).rolling(..).apply()` (`RollingGroupby`) where the `raw` parameter was ignored (GH31754)
- Fixed regression in *`rolling(..).corr()`* when using a time offset (GH31789)
- Fixed regression in *`groupby(..).nunique()`* which was modifying the original values if `NaN` values were present (GH31950)
- Fixed regression in `DataFrame.groupby` raising a `ValueError` from an internal operation (GH31802)
- Fixed regression in *`groupby(..).agg()`* calling a user-provided function an extra time on an empty input (GH31760)

I/O

- Fixed regression in *read_csv()* in which the encoding option was not recognized with certain file-like objects (GH31819)
- Fixed regression in *DataFrame.to_excel()* when the columns keyword argument is passed (GH31677)
- Fixed regression in ExcelFile where the stream passed into the function was closed by the destructor. (GH31467)
- Fixed regression where *read_pickle()* raised a UnicodeDecodeError when reading a py27 pickle with *MultiIndex* column (GH31988).

Reindexing/alignment

- Fixed regression in *Series.align()* when other is a *DataFrame* and method is not None (GH31785)
- Fixed regression in *DataFrame.reindex()* and *Series.reindex()* when reindexing with (tz-aware) index and method=nearest (GH26683)
- Fixed regression in *DataFrame.reindex_like()* on a *DataFrame* subclass raised an AssertionError (GH31925)
- Fixed regression in *DataFrame* arithmetic operations with mis-matched columns (GH31623)

Other

- Fixed regression in joining on *DatetimeIndex* or *TimedeltaIndex* to preserve freq in simple cases (GH32166)
- Fixed regression in *Series.shift()* with datetime64 dtype when passing an integer fill_value (GH32591)
- Fixed regression in the repr of an object-dtype *Index* with bools and missing values (GH32146)

Indexing with nullable boolean arrays

Previously indexing with a nullable Boolean array containing NA would raise a ValueError, however this is now permitted with NA being treated as False. (GH31503)

```
In [1]: s = pd.Series([1, 2, 3, 4])

In [2]: mask = pd.array([True, True, False, None], dtype="boolean")

In [3]: s
Out[3]:
0    1
1    2
2    3
3    4
Length: 4, dtype: int64

In [4]: mask
Out[4]:
<BooleanArray>
[True, True, False, <NA>]
Length: 4, dtype: boolean
```

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```
>>> s[mask]
Traceback (most recent call last):
```

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```
...
ValueError: cannot mask with array containing NA / NaN values
```

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```
In [5]: s[mask]
Out[5]:
0    1
1    2
Length: 2, dtype: int64
```

Bug fixes

Datetimelike

- Bug in *Series.astype()* not copying for tz-naive and tz-aware `datetime64` dtype (GH32490)
- Bug where *to_datetime()* would raise when passed `pd.NA` (GH32213)
- Improved error message when subtracting two *Timestamp* that result in an out-of-bounds *Timedelta* (GH31774)

Categorical

- Fixed bug where *Categorical.from_codes()* improperly raised a `ValueError` when passed nullable integer codes. (GH31779)
- Fixed bug where *Categorical()* constructor would raise a `TypeError` when given a numpy array containing `pd.NA`. (GH31927)
- Bug in *Categorical* that would ignore or crash when calling *Series.replace()* with a list-like `to_replace` (GH31720)

I/O

- Using `pd.NA` with *DataFrame.to_json()* now correctly outputs a null value instead of an empty object (GH31615)
- Bug in *pandas.json_normalize()* when value in meta path is not iterable (GH31507)
- Fixed pickling of `pandas.NA`. Previously a new object was returned, which broke computations relying on `NA` being a singleton (GH31847)
- Fixed bug in parquet roundtrip with nullable unsigned integer dtypes (GH31896).

Experimental dtypes

- Fixed bug in *DataFrame.convert_dtypes()* for columns that were already using the `"string"` dtype (GH31731).
- Fixed bug in *DataFrame.convert_dtypes()* for series with mix of integers and strings (GH32117)
- Fixed bug in *DataFrame.convert_dtypes()* where `BooleanDtype` columns were converted to `Int64` (GH32287)
- Fixed bug in setting values using a slice indexer with string dtype (GH31772)
- Fixed bug where *pandas.core.groupby.GroupBy.first()* and *pandas.core.groupby.GroupBy.last()* would raise a `TypeError` when groups contained `pd.NA` in a column of object dtype (GH32123)

- Fixed bug where `DataFrameGroupBy.mean()`, `DataFrameGroupBy.median()`, `DataFrameGroupBy.var()`, and `DataFrameGroupBy.std()` would raise a `TypeError` on `Int64` dtype columns (GH32219)

Strings

- Using `pd.NA` with *`Series.str.repeat()`* now correctly outputs a null value instead of raising error for vector inputs (GH31632)

Rolling

- Fixed rolling operations with variable window (defined by time duration) on decreasing time index (GH32385).

Contributors

A total of 25 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Justin Zheng
- Kaiqi Dong
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- Simon Hawkins
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5.3.5 What's new in 1.0.1 (February 5, 2020)

These are the changes in pandas 1.0.1. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in *DataFrame* setting values with a slice (e.g. `df[-4:] = 1`) indexing by label instead of position (GH31469)
- Fixed regression when indexing a `Series` or `DataFrame` indexed by `DatetimeIndex` with a slice containing a `datetime.date` (GH31501)
- Fixed regression in `DataFrame.__setitem__` raising an `AttributeError` with a *MultiIndex* and a non-monotonic indexer (GH31449)
- Fixed regression in *Series* multiplication when multiplying a numeric *Series* with >10000 elements with a timedelta-like scalar (GH31457)
- Fixed regression in `.groupby().agg()` raising an `AssertionError` for some reductions like `min` on object-dtype columns (GH31522)
- Fixed regression in `.groupby()` aggregations with categorical dtype using Cythonized reduction functions (e.g. `first`) (GH31450)
- Fixed regression in `GroupBy.apply()` if called with a function which returned a non-pandas non-scalar object (e.g. a list or numpy array) (GH31441)
- Fixed regression in *DataFrame.groupby()* whereby taking the minimum or maximum of a column with period dtype would raise a `TypeError`. (GH31471)
- Fixed regression in *DataFrame.groupby()* with an empty DataFrame grouping by a level of a MultiIndex (GH31670).
- Fixed regression in *DataFrame.apply()* with object dtype and non-reducing function (GH31505)
- Fixed regression in *to_datetime()* when parsing non-nanosecond resolution datetimes (GH31491)
- Fixed regression in *to_csv()* where specifying an `na_rep` might truncate the values written (GH31447)
- Fixed regression in *Categorical* construction with `numpy.str_` categories (GH31499)
- Fixed regression in *DataFrame.loc()* and *DataFrame.iloc()* when selecting a row containing a single `datetime64` or `timedelta64` column (GH31649)
- Fixed regression where setting `pd.options.display.max_colwidth` was not accepting negative integer. In addition, this behavior has been deprecated in favor of using `None` (GH31532)
- Fixed regression in objTOJSON.c fix return-type warning (GH31463)
- Fixed regression in *qcut()* when passed a nullable integer. (GH31389)
- Fixed regression in assigning to a *Series* using a nullable integer dtype (GH31446)
- Fixed performance regression when indexing a `DataFrame` or `Series` with a *MultiIndex* for the index using a list of labels (GH31648)
- Fixed regression in *read_csv()* used in file like object `RawIOBase` is not recognize `encoding` option (GH31575)

Deprecations

- Support for negative integer for `pd.options.display.max_colwidth` is deprecated in favor of using `None` (GH31532)

Bug fixes

Datetimelike

- Fixed bug in *`to_datetime()`* raising when `cache=True` and out-of-bound values are present (GH31491)

Numeric

- Bug in dtypes being lost in `DataFrame.__invert__` (~ operator) with mixed dtypes (GH31183) and for extension-array backed `Series` and `DataFrame` (GH23087)

Plotting

- Plotting tz-aware timeseries no longer gives UserWarning (GH31205)

Interval

- Bug in *`Series.shift()`* with `interval` dtype raising a `TypeError` when shifting an interval array of integers or datetimes (GH34195)

Contributors

A total of 15 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Kaiqi Dong
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- Tom Augspurger
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- proost

5.3.6 What's new in 1.0.0 (January 29, 2020)

These are the changes in pandas 1.0.0. See *Release notes* for a full changelog including other versions of pandas.

Note: The pandas 1.0 release removed a lot of functionality that was deprecated in previous releases (see *below* for an overview). It is recommended to first upgrade to pandas 0.25 and to ensure your code is working without warnings, before upgrading to pandas 1.0.

New deprecation policy

Starting with pandas 1.0.0, pandas will adopt a variant of SemVer to version releases. Briefly,

- Deprecations will be introduced in minor releases (e.g. 1.1.0, 1.2.0, 2.1.0, ...)
- Deprecations will be enforced in major releases (e.g. 1.0.0, 2.0.0, 3.0.0, ...)
- API-breaking changes will be made only in major releases (except for experimental features)

See *Version policy* for more.

Enhancements

Using Numba in `rolling.apply` and `expanding.apply`

We've added an `engine` keyword to *`apply()`* and *`apply()`* that allows the user to execute the routine using Numba instead of Cython. Using the Numba engine can yield significant performance gains if the apply function can operate on numpy arrays and the data set is larger (1 million rows or greater). For more details, see *rolling apply documentation* (GH28987, GH30936)

Defining custom windows for rolling operations

We've added a *`pandas.api.indexers.BaseIndexer()`* class that allows users to define how window bounds are created during `rolling` operations. Users can define their own `get_window_bounds` method on a *`pandas.api.indexers.BaseIndexer()`* subclass that will generate the start and end indices used for each window during the rolling aggregation. For more details and example usage, see the *custom window rolling documentation*

Converting to markdown

We've added *`to_markdown()`* for creating a markdown table (GH11052)

```
In [1]: df = pd.DataFrame({"A": [1, 2, 3], "B": [1, 2, 3]}, index=['a', 'a', 'b'])

In [2]: print(df.to_markdown())
|    |   A |   B |
|:---|----:|----:|
| a  |   1 |   1 |
| a  |   2 |   2 |
| b  |   3 |   3 |
```

Experimental new features

Experimental NA scalar to denote missing values

A new `pd.NA` value (singleton) is introduced to represent scalar missing values. Up to now, pandas used several values to represent missing data: `np.nan` is used for this for float data, `np.nan` or `None` for object-dtype data and `pd.NaT` for datetime-like data. The goal of `pd.NA` is to provide a "missing" indicator that can be used consistently across data types. `pd.NA` is currently used by the nullable integer and boolean data types and the new string data type (GH28095).

Warning: Experimental: the behaviour of `pd.NA` can still change without warning.

For example, creating a Series using the nullable integer dtype:

```
In [3]: s = pd.Series([1, 2, None], dtype="Int64")

In [4]: s
Out[4]:
0       1
1       2
2    <NA>
Length: 3, dtype: Int64

In [5]: s[2]
Out[5]: <NA>
```

Compared to `np.nan`, `pd.NA` behaves differently in certain operations. In addition to arithmetic operations, `pd.NA` also propagates as "missing" or "unknown" in comparison operations:

```
In [6]: np.nan > 1
Out[6]: False

In [7]: pd.NA > 1
Out[7]: <NA>
```

For logical operations, `pd.NA` follows the rules of the three-valued logic (or *Kleene logic*). For example:

```
In [8]: pd.NA | True
Out[8]: True
```

For more, see *NA section* in the user guide on missing data.

Dedicated string data type

We've added *`StringDtype`*, an extension type dedicated to string data. Previously, strings were typically stored in object-dtype NumPy arrays. (GH29975)

Warning: `StringDtype` is currently considered experimental. The implementation and parts of the API may change without warning.

The `'string'` extension type solves several issues with object-dtype NumPy arrays:

1. You can accidentally store a *mixture* of strings and non-strings in an `object` dtype array. A `StringArray` can only store strings.
2. `object` dtype breaks dtype-specific operations like *`DataFrame.select_dtypes()`*. There isn't a clear way to select *just* text while excluding non-text, but still object-dtype columns.
3. When reading code, the contents of an `object` dtype array is less clear than `string`.

```
In [9]: pd.Series(['abc', None, 'def'], dtype=pd.StringDtype())
Out[9]:
0     abc
1    <NA>
2     def
Length: 3, dtype: string
```

You can use the alias `"string"` as well.

```
In [10]: s = pd.Series(['abc', None, 'def'], dtype="string")

In [11]: s
Out[11]:
0     abc
1    <NA>
2     def
Length: 3, dtype: string
```

The usual string accessor methods work. Where appropriate, the return type of the Series or columns of a DataFrame will also have string dtype.

```
In [12]: s.str.upper()
Out[12]:
0     ABC
1    <NA>
2     DEF
Length: 3, dtype: string

In [13]: s.str.split('b', expand=True).dtypes
Out[13]:
0    string
1    string
Length: 2, dtype: object
```

String accessor methods returning integers will return a value with *`Int64Dtype`*

```
In [14]: s.str.count("a")
Out[14]:
0       1
1    <NA>
2       0
Length: 3, dtype: Int64
```

We recommend explicitly using the `string` data type when working with strings. See *Text data types* for more.

Boolean data type with missing values support

We've added *BooleanDtype* / *BooleanArray*, an extension type dedicated to boolean data that can hold missing values. The default `bool` data type based on a bool-dtype NumPy array, the column can only hold `True` or `False`, and not missing values. This new *BooleanArray* can store missing values as well by keeping track of this in a separate mask. (GH29555, GH30095, GH31131)

```
In [15]: pd.Series([True, False, None], dtype=pd.BooleanDtype())
Out[15]:
0     True
1    False
2     <NA>
Length: 3, dtype: boolean
```

You can use the alias `"boolean"` as well.

```
In [16]: s = pd.Series([True, False, None], dtype="boolean")

In [17]: s
Out[17]:
0     True
1    False
2     <NA>
Length: 3, dtype: boolean
```

Method `convert_dtypes` to ease use of supported extension dtypes

In order to encourage use of the extension dtypes `StringDtype`, `BooleanDtype`, `Int64Dtype`, `Int32Dtype`, etc., that support `pd.NA`, the methods *DataFrame.convert_dtypes()* and *Series.convert_dtypes()* have been introduced. (GH29752) (GH30929)

Example:

```
In [18]: df = pd.DataFrame({'x': ['abc', None, 'def'],
   ....:                    'y': [1, 2, np.nan],
   ....:                    'z': [True, False, True]})
   ....:

In [19]: df
Out[19]:
      x    y      z
0   abc  1.0   True
1  None  2.0  False
2   def  NaN   True

[3 rows x 3 columns]

In [20]: df.dtypes
Out[20]:
x     object
y    float64
z       bool
Length: 3, dtype: object
```

```
In [21]: converted = df.convert_dtypes()

In [22]: converted
Out[22]:
      x     y      z
0   abc     1   True
1  <NA>     2  False
2   def  <NA>   True

[3 rows x 3 columns]

In [23]: converted.dtypes
Out[23]:
x     string
y      Int64
z    boolean
Length: 3, dtype: object
```

This is especially useful after reading in data using readers such as *read_csv()* and *read_excel()*. See *here* for a description.

Other enhancements

- *DataFrame.to_string()* added the `max_colwidth` parameter to control when wide columns are truncated (GH9784)
- Added the `na_value` argument to *Series.to_numpy()*, *Index.to_numpy()* and *DataFrame.to_numpy()* to control the value used for missing data (GH30322)
- *MultiIndex.from_product()* infers level names from inputs if not explicitly provided (GH27292)
- *DataFrame.to_latex()* now accepts `caption` and `label` arguments (GH25436)
- DataFrames with *nullable integer*, the *new string dtype* and period data type can now be converted to `pyarrow` (>=0.15.0), which means that it is supported in writing to the Parquet file format when using the `pyarrow` engine (GH28368). Full roundtrip to parquet (writing and reading back in with *to_parquet()* / *read_parquet()*) is supported starting with pyarrow >= 0.16 (GH20612).
- `to_parquet()` now appropriately handles the `schema` argument for user defined schemas in the pyarrow engine. (GH30270)
- *DataFrame.to_json()* now accepts an `indent` integer argument to enable pretty printing of JSON output (GH12004)
- *read_stata()* can read Stata 119 dta files. (GH28250)
- Implemented `pandas.core.window.Window.var()` and `pandas.core.window.Window.std()` functions (GH26597)
- Added `encoding` argument to *DataFrame.to_string()* for non-ascii text (GH28766)
- Added `encoding` argument to *DataFrame.to_html()* for non-ascii text (GH28663)
- `Styler.background_gradient()` now accepts `vmin` and `vmax` arguments (GH12145)
- `Styler.format()` added the `na_rep` parameter to help format the missing values (GH21527, GH28358)
- *read_excel()* now can read binary Excel (`.xlsb`) files by passing `engine='pyxlsb'`. For more details and example usage, see the *Binary Excel files documentation*. Closes GH8540.
- The `partition_cols` argument in *DataFrame.to_parquet()* now accepts a string (GH27117)

- *pandas.read_json()* now parses NaN, Infinity and -Infinity (GH12213)
- DataFrame constructor preserve ExtensionArray dtype with ExtensionArray (GH11363)
- *DataFrame.sort_values()* and *Series.sort_values()* have gained ignore_index keyword to be able to reset index after sorting (GH30114)
- *DataFrame.sort_index()* and *Series.sort_index()* have gained ignore_index keyword to reset index (GH30114)
- *DataFrame.drop_duplicates()* has gained ignore_index keyword to reset index (GH30114)
- Added new writer for exporting Stata dta files in versions 118 and 119, StataWriterUTF8. These files formats support exporting strings containing Unicode characters. Format 119 supports data sets with more than 32,767 variables (GH23573, GH30959)
- *Series.map()* now accepts collections.abc.Mapping subclasses as a mapper (GH29733)
- Added an experimental *attrs* for storing global metadata about a dataset (GH29062)
- *Timestamp.fromisocalendar()* is now compatible with python 3.8 and above (GH28115)
- *DataFrame.to_pickle()* and *read_pickle()* now accept URL (GH30163)

Backwards incompatible API changes

Avoid using names from MultiIndex.levels

As part of a larger refactor to *MultiIndex* the level names are now stored separately from the levels (GH27242). We recommend using *MultiIndex.names* to access the names, and *Index.set_names()* to update the names.

For backwards compatibility, you can still *access* the names via the levels.

```
In [24]: mi = pd.MultiIndex.from_product([[1, 2], ['a', 'b']], names=['x', 'y'])

In [25]: mi.levels[0].name
Out[25]: 'x'
```

However, it is no longer possible to *update* the names of the MultiIndex via the level.

```
In [26]: mi.levels[0].name = "new name"
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
<ipython-input-26-65f4400a0c97> in <module>
----> 1 mi.levels[0].name = "new name"

/pandas/pandas/core/indexes/base.py in name(self, value)
   1241         if self._no_setting_name:
   1242             # Used in MultiIndex.levels to avoid silently ignoring name␣
↪updates.
-> 1243             raise RuntimeError(
   1244                 "Cannot set name on a level of a MultiIndex. Use "
   1245                 "'MultiIndex.set_names' instead."

RuntimeError: Cannot set name on a level of a MultiIndex. Use 'MultiIndex.set_names'␣
↪instead.

In [27]: mi.names
Out[27]: FrozenList(['x', 'y'])
```

To update, use `MultiIndex.set_names`, which returns a new `MultiIndex`.

```
In [28]: mi2 = mi.set_names("new name", level=0)

In [29]: mi2.names
Out[29]: FrozenList(['new name', 'y'])
```

New repr for `IntervalArray`

pandas.arrays.IntervalArray adopts a new `__repr__` in accordance with other array classes (GH25022)

pandas 0.25.x

```
In [1]: pd.arrays.IntervalArray.from_tuples([(0, 1), (2, 3)])
Out[2]:
IntervalArray([(0, 1], (2, 3]],
              closed='right',
              dtype='interval[int64]')
```

pandas 1.0.0

```
In [30]: pd.arrays.IntervalArray.from_tuples([(0, 1), (2, 3)])
Out[30]:
<IntervalArray>
[(0, 1], (2, 3]]
Length: 2, closed: right, dtype: interval[int64]
```

`DataFrame.rename` now only accepts one positional argument

DataFrame.rename() would previously accept positional arguments that would lead to ambiguous or undefined behavior. From pandas 1.0, only the very first argument, which maps labels to their new names along the default axis, is allowed to be passed by position (GH29136).

pandas 0.25.x

```
>>> df = pd.DataFrame([[1]])
>>> df.rename({0: 1}, {0: 2})
FutureWarning: ...Use named arguments to resolve ambiguity...
   2
1  1
```

pandas 1.0.0

```
>>> df.rename({0: 1}, {0: 2})
Traceback (most recent call last):
...
TypeError: rename() takes from 1 to 2 positional arguments but 3 were given
```

Note that errors will now be raised when conflicting or potentially ambiguous arguments are provided.

pandas 0.25.x

```
>>> df.rename({0: 1}, index={0: 2})
   0
1  1
```

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```
>>> df.rename(mapper={0: 1}, index={0: 2})
   0
2  1
```

pandas 1.0.0

```
>>> df.rename({0: 1}, index={0: 2})
Traceback (most recent call last):
...
TypeError: Cannot specify both 'mapper' and any of 'index' or 'columns'

>>> df.rename(mapper={0: 1}, index={0: 2})
Traceback (most recent call last):
...
TypeError: Cannot specify both 'mapper' and any of 'index' or 'columns'
```

You can still change the axis along which the first positional argument is applied by supplying the `axis` keyword argument.

```
In [31]: df.rename({0: 1})
Out[31]:
   0
1  1

[1 rows x 1 columns]

In [32]: df.rename({0: 1}, axis=1)
Out[32]:
   1
0  1

[1 rows x 1 columns]
```

If you would like to update both the index and column labels, be sure to use the respective keywords.

```
In [33]: df.rename(index={0: 1}, columns={0: 2})
Out[33]:
   2
1  1

[1 rows x 1 columns]
```

Extended verbose info output for `DataFrame`

`DataFrame.info()` now shows line numbers for the columns summary (GH17304)

pandas 0.25.x

```
>>> df = pd.DataFrame({"int_col": [1, 2, 3],
...                    "text_col": ["a", "b", "c"],
...                    "float_col": [0.0, 0.1, 0.2]})
>>> df.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
```

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```
Data columns (total 3 columns):
int_col      3 non-null int64
text_col     3 non-null object
float_col    3 non-null float64
dtypes: float64(1), int64(1), object(1)
memory usage: 152.0+ bytes
```

pandas 1.0.0

```
In [34]: df = pd.DataFrame({"int_col": [1, 2, 3],
   ....:                    "text_col": ["a", "b", "c"],
   ....:                    "float_col": [0.0, 0.1, 0.2]})
   ....:

In [35]: df.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   int_col    3 non-null      int64
 1   text_col   3 non-null      object
 2   float_col  3 non-null      float64
dtypes: float64(1), int64(1), object(1)
memory usage: 200.0+ bytes
```

`pandas.array()` inference changes

pandas.array() now infers pandas' new extension types in several cases (GH29791):

1. String data (including missing values) now returns a *arrays.StringArray*.
2. Integer data (including missing values) now returns a *arrays.IntegerArray*.
3. Boolean data (including missing values) now returns the new *arrays.BooleanArray*

pandas 0.25.x

```
>>> pd.array(["a", None])
<PandasArray>
['a', None]
Length: 2, dtype: object

>>> pd.array([1, None])
<PandasArray>
[1, None]
Length: 2, dtype: object
```

pandas 1.0.0

```
In [36]: pd.array(["a", None])
Out[36]:
<StringArray>
['a', <NA>]
Length: 2, dtype: string
```

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```
In [37]: pd.array([1, None])
Out[37]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64
```

As a reminder, you can specify the `dtype` to disable all inference.

`arrays.IntegerArray` now uses `pandas.NA`

arrays.IntegerArray now uses `pandas.NA` rather than `numpy.nan` as its missing value marker (GH29964).

pandas 0.25.x

```
>>> a = pd.array([1, 2, None], dtype="Int64")
>>> a
<IntegerArray>
[1, 2, NaN]
Length: 3, dtype: Int64

>>> a[2]
nan
```

pandas 1.0.0

```
In [38]: a = pd.array([1, 2, None], dtype="Int64")

In [39]: a
Out[39]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64

In [40]: a[2]
Out[40]: <NA>
```

This has a few API-breaking consequences.

Converting to a NumPy ndarray

When converting to a NumPy array missing values will be `pd.NA`, which cannot be converted to a float. So calling `np.asarray(integer_array, dtype="float")` will now raise.

pandas 0.25.x

```
>>> np.asarray(a, dtype="float")
array([ 1.,  2., nan])
```

pandas 1.0.0

```
In [41]: np.asarray(a, dtype="float")
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-41-4578f04da2b3> in <module>
----> 1 np.asarray(a, dtype="float")
```

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```
/opt/conda/envs/pandas/lib/python3.8/site-packages/numpy/core/_asarray.py in␣
↪asarray(a, dtype, order, like)
    100         return _asarray_with_like(a, dtype=dtype, order=order, like=like)
    101
--> 102     return array(a, dtype, copy=False, order=order)
    103
    104

/pandas/pandas/core/arrays/masked.py in __array__(self, dtype)
    237         We return an object array here to preserve our scalar values
    238         """
--> 239         return self.to_numpy(dtype=dtype)
    240
    241     def __arrow_array__(self, type=None):

/pandas/pandas/core/arrays/masked.py in to_numpy(self, dtype, copy, na_value)
    218                 and na_value is libmissing.NA
    219             ):
--> 220                 raise ValueError(
    221                     f"cannot convert to '{dtype}'-dtype NumPy array "
    222                     "with missing values. Specify an appropriate 'na_value' "

ValueError: cannot convert to 'float64'-dtype NumPy array with missing values.␣
↪Specify an appropriate 'na_value' for this dtype.
```

Use `arrays.IntegerArray.to_numpy()` with an explicit `na_value` instead.

```
In [42]: a.to_numpy(dtype="float", na_value=np.nan)
Out[42]: array([ 1.,  2., nan])
```

Reductions can return ``pd.NA``

When performing a reduction such as a sum with `skipna=False`, the result will now be `pd.NA` instead of `np.nan` in presence of missing values (GH30958).

pandas 0.25.x

```
>>> pd.Series(a).sum(skipna=False)
nan
```

pandas 1.0.0

```
In [43]: pd.Series(a).sum(skipna=False)
Out[43]: <NA>
```

value_counts returns a nullable integer dtype

`Series.value_counts()` with a nullable integer dtype now returns a nullable integer dtype for the values.

pandas 0.25.x

```
>>> pd.Series([2, 1, 1, None], dtype="Int64").value_counts().dtype
dtype('int64')
```

pandas 1.0.0

```
In [44]: pd.Series([2, 1, 1, None], dtype="Int64").value_counts().dtype
Out[44]: Int64Dtype()
```

See *Experimental NA scalar to denote missing values* for more on the differences between `pandas.NA` and `numpy.nan`.

`arrays.IntegerArray` comparisons return `arrays.BooleanArray`

Comparison operations on a *`arrays.IntegerArray`* now returns a *`arrays.BooleanArray`* rather than a NumPy array (GH29964).

pandas 0.25.x

```
>>> a = pd.array([1, 2, None], dtype="Int64")
>>> a
<IntegerArray>
[1, 2, NaN]
Length: 3, dtype: Int64

>>> a > 1
array([False,  True, False])
```

pandas 1.0.0

```
In [45]: a = pd.array([1, 2, None], dtype="Int64")

In [46]: a > 1
Out[46]:
<BooleanArray>
[False, True, <NA>]
Length: 3, dtype: boolean
```

Note that missing values now propagate, rather than always comparing unequal like `numpy.nan`. See *Experimental NA scalar to denote missing values* for more.

By default `Categorical.min()` now returns the minimum instead of np.nan

When *`Categorical`* contains `np.nan`, `Categorical.min()` no longer return `np.nan` by default (skipna=True) (GH25303)

pandas 0.25.x

```
In [1]: pd.Categorical([1, 2, np.nan], ordered=True).min()
Out[1]: nan
```

pandas 1.0.0

```
In [47]: pd.Categorical([1, 2, np.nan], ordered=True).min()
Out[47]: 1
```

Default dtype of empty `pandas.Series`

Initialising an empty *pandas.Series* without specifying a dtype will raise a `DeprecationWarning` now (GH17261). The default dtype will change from `float64` to `object` in future releases so that it is consistent with the behaviour of *DataFrame* and *Index*.

pandas 1.0.0

```
In [1]: pd.Series()
Out[2]:
DeprecationWarning: The default dtype for empty Series will be 'object' instead of
↪'float64' in a future version. Specify a dtype explicitly to silence this warning.
Series([], dtype: float64)
```

Result dtype inference changes for resample operations

The rules for the result dtype in *DataFrame.resample()* aggregations have changed for extension types (GH31359). Previously, pandas would attempt to convert the result back to the original dtype, falling back to the usual inference rules if that was not possible. Now, pandas will only return a result of the original dtype if the scalar values in the result are instances of the extension dtype's scalar type.

```
In [48]: df = pd.DataFrame({"A": ['a', 'b']}, dtype='category',
   ....:                   index=pd.date_range('2000', periods=2))
   ....:

In [49]: df
Out[49]:
             A
2000-01-01   a
2000-01-02   b

[2 rows x 1 columns]
```

pandas 0.25.x

```
>>> df.resample("2D").agg(lambda x: 'a').A.dtype
CategoricalDtype(categories=['a', 'b'], ordered=False)
```

pandas 1.0.0

```
In [50]: df.resample("2D").agg(lambda x: 'a').A.dtype
Out[50]: dtype('O')
```

This fixes an inconsistency between `resample` and `groupby`. This also fixes a potential bug, where the **values** of the result might change depending on how the results are cast back to the original dtype.

pandas 0.25.x

```
>>> df.resample("2D").agg(lambda x: 'c')

     A
0  NaN
```

pandas 1.0.0

```
In [51]: df.resample("2D").agg(lambda x: 'c')
Out[51]:
              A
2000-01-01  c

[1 rows x 1 columns]
```

Increased minimum version for Python

pandas 1.0.0 supports Python 3.6.1 and higher (GH29212).

Increased minimum versions for dependencies

Some minimum supported versions of dependencies were updated (GH29766, GH29723). If installed, we now require:

Package	Minimum Version	Required	Changed
numpy	1.13.3	X	
pytz	2015.4	X	
python-dateutil	2.6.1	X	
bottleneck	1.2.1		
numexpr	2.6.2		
pytest (dev)	4.0.2		

For optional libraries the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

Package	Minimum Version	Changed
beautifulsoup4	4.6.0	
fastparquet	0.3.2	X
gcsfs	0.2.2	
lxml	3.8.0	
matplotlib	2.2.2	
numba	0.46.0	X
openpyxl	2.5.7	X
pyarrow	0.13.0	X
pymysql	0.7.1	
pytables	3.4.2	
s3fs	0.3.0	X
scipy	0.19.0	
sqlalchemy	1.1.4	
xarray	0.8.2	
xlrd	1.1.0	
xlsxwriter	0.9.8	
xlwt	1.2.0	

See *Dependencies* and *Optional dependencies* for more.

Build changes

pandas has added a pyproject.toml file and will no longer include cythonized files in the source distribution uploaded to PyPI (GH28341, GH20775). If you're installing a built distribution (wheel) or via conda, this shouldn't have any effect on you. If you're building pandas from source, you should no longer need to install Cython into your build environment before calling `pip install pandas`.

Other API changes

- `core.groupby.GroupBy.transform` now raises on invalid operation names (GH27489)
- *`pandas.api.types.infer_dtype()`* will now return "integer-na" for integer and `np.nan` mix (GH27283)
- *`MultiIndex.from_arrays()`* will no longer infer names from arrays if `names=None` is explicitly provided (GH27292)
- In order to improve tab-completion, pandas does not include most deprecated attributes when introspecting a pandas object using `dir` (e.g. `dir(df)`). To see which attributes are excluded, see an object's `_deprecations` attribute, for example `pd.DataFrame._deprecations` (GH28805).
- The returned dtype of *`unique()`* now matches the input dtype. (GH27874)
- Changed the default configuration value for `options.matplotlib.register_converters` from `True` to `"auto"` (GH18720). Now, pandas custom formatters will only be applied to plots created by pandas, through *`plot()`*. Previously, pandas' formatters would be applied to all plots created *after* a *`plot()`*. See *units registration* for more.
- *`Series.dropna()`* has dropped its `**kwargs` argument in favor of a single `how` parameter. Supplying anything else than `how` to `**kwargs` raised a `TypeError` previously (GH29388)
- When testing pandas, the new minimum required version of pytest is 5.0.1 (GH29664)
- `Series.str.__iter__()` was deprecated and will be removed in future releases (GH28277).
- Added `<NA>` to the list of default NA values for *`read_csv()`* (GH30821)

Documentation improvements

- Added new section on *Scaling to large datasets* (GH28315).
- Added sub-section on *Query MultiIndex* for HDF5 datasets (GH28791).

Deprecations

- *`Series.item()`* and *`Index.item()`* have been _undeprecated_ (GH29250)
- `Index.set_value` has been deprecated. For a given index `idx`, array `arr`, value in `idx` of `idx_val` and a new value of `val`, `idx.set_value(arr, idx_val, val)` is equivalent to `arr[idx.get_loc(idx_val)] = val`, which should be used instead (GH28621).
- `is_extension_type()` is deprecated, `is_extension_array_dtype()` should be used instead (GH29457)
- *`eval()`* keyword argument "truediv" is deprecated and will be removed in a future version (GH29812)

- `DateOffset.isAnchored()` and `DatetOffset.onOffset()` are deprecated and will be removed in a future version, use `DateOffset.is_anchored()` and `DateOffset.is_on_offset()` instead (GH30340)
- `pandas.tseries.frequencies.get_offset` is deprecated and will be removed in a future version, use `pandas.tseries.frequencies.to_offset` instead (GH4205)
- `Categorical.take_nd()` and `CategoricalIndex.take_nd()` are deprecated, use `Categorical.take()` and `CategoricalIndex.take()` instead (GH27745)
- The parameter `numeric_only` of `Categorical.min()` and `Categorical.max()` is deprecated and replaced with `skipna` (GH25303)
- The parameter `label` in `lreshape()` has been deprecated and will be removed in a future version (GH29742)
- `pandas.core.index` has been deprecated and will be removed in a future version, the public classes are available in the top-level namespace (GH19711)
- *`pandas.json_normalize()`* is now exposed in the top-level namespace. Usage of `json_normalize` as `pandas.io.json.json_normalize` is now deprecated and it is recommended to use `json_normalize` as *`pandas.json_normalize()`* instead (GH27586).
- The `numpy` argument of *`pandas.read_json()`* is deprecated (GH28512).
- *`DataFrame.to_stata()`*, *`DataFrame.to_feather()`*, and *`DataFrame.to_parquet()`* argument "fname" is deprecated, use "path" instead (GH23574)
- The deprecated internal attributes `_start`, `_stop` and `_step` of *`RangeIndex`* now raise a `FutureWarning` instead of a `DeprecationWarning` (GH26581)
- The `pandas.util.testing` module has been deprecated. Use the public API in `pandas.testing` documented at *Testing functions* (GH16232).
- `pandas.SparseArray` has been deprecated. Use `pandas.arrays.SparseArray` (*`arrays.SparseArray`*) instead. (GH30642)
- The parameter `is_copy` of *`Series.take()`* and *`DataFrame.take()`* has been deprecated and will be removed in a future version. (GH27357)
- Support for multi-dimensional indexing (e.g. `index[:, None]`) on a *`Index`* is deprecated and will be removed in a future version, convert to a numpy array before indexing instead (GH30588)
- The `pandas.np` submodule is now deprecated. Import numpy directly instead (GH30296)
- The `pandas.datetime` class is now deprecated. Import from `datetime` instead (GH30610)
- *`diff`* will raise a `TypeError` rather than implicitly losing the dtype of extension types in the future. Convert to the correct dtype before calling `diff` instead (GH31025)

Selecting Columns from a Grouped DataFrame

When selecting columns from a `DataFrameGroupBy` object, passing individual keys (or a tuple of keys) inside single brackets is deprecated, a list of items should be used instead. (GH23566) For example:

```
df = pd.DataFrame({
    "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],
    "B": np.random.randn(8),
    "C": np.random.randn(8),
})
g = df.groupby('A')

# single key, returns SeriesGroupBy
```

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```
g['B']

# tuple of single key, returns SeriesGroupBy
g[('B',)]

# tuple of multiple keys, returns DataFrameGroupBy, raises FutureWarning
g[('B', 'C')]

# multiple keys passed directly, returns DataFrameGroupBy, raises FutureWarning
# (implicitly converts the passed strings into a single tuple)
g['B', 'C']

# proper way, returns DataFrameGroupBy
g[['B', 'C']]
```

Removal of prior version deprecations/changes

Removed SparseSeries and SparseDataFrame

`SparseSeries`, `SparseDataFrame` and the `DataFrame.to_sparse` method have been removed (GH28425). We recommend using a `Series` or `DataFrame` with sparse values instead. See *Migrating* for help with migrating existing code.

Matplotlib unit registration

Previously, pandas would register converters with matplotlib as a side effect of importing pandas (GH18720). This changed the output of plots made via matplotlib plots after pandas was imported, even if you were using matplotlib directly rather than *plot()*.

To use pandas formatters with a matplotlib plot, specify

```
>>> import pandas as pd
>>> pd.options.plotting.matplotlib.register_converters = True
```

Note that plots created by *DataFrame.plot()* and *Series.plot()* *do* register the converters automatically. The only behavior change is when plotting a date-like object via `matplotlib.pyplot.plot` or `matplotlib.Axes.plot`. See *Custom formatters for timeseries plots* for more.

Other removals

- Removed the previously deprecated keyword "index" from *read_stata()*, `StataReader`, and `StataReader.read()`, use "index_col" instead (GH17328)
- Removed `StataReader.data` method, use `StataReader.read()` instead (GH9493)
- Removed `pandas.plotting._matplotlib.tsplot`, use *Series.plot()* instead (GH19980)
- `pandas.tseries.converter.register` has been moved to *pandas.plotting.register_matplotlib_converters()* (GH18307)
- *Series.plot()* no longer accepts positional arguments, pass keyword arguments instead (GH30003)
- *DataFrame.hist()* and *Series.hist()* no longer allows `figsize="default"`, specify figure size by passinig a tuple instead (GH30003)
- Floordiv of integer-dtyped array by *Timedelta* now raises `TypeError` (GH21036)
- *TimedeltaIndex* and *DatetimeIndex* no longer accept non-nanosecond dtype strings like "timedelta64" or "datetime64", use "timedelta64[ns]" and "datetime64[ns]" instead (GH24806)

- Changed the default "skipna" argument in *pandas.api.types.infer_dtype()* from `False` to `True` (GH24050)
- Removed `Series.ix` and `DataFrame.ix` (GH26438)
- Removed `Index.summary` (GH18217)
- Removed the previously deprecated keyword "fastpath" from the *Index* constructor (GH23110)
- Removed `Series.get_value`, `Series.set_value`, `DataFrame.get_value`, `DataFrame.set_value` (GH17739)
- Removed `Series.compound` and `DataFrame.compound` (GH26405)
- Changed the default "inplace" argument in *DataFrame.set_index()* and *Series.set_axis()* from `None` to `False` (GH27600)
- Removed `Series.cat.categorical`, `Series.cat.index`, `Series.cat.name` (GH24751)
- Removed the previously deprecated keyword "box" from *to_datetime()* and *to_timedelta()*; in addition these now always returns *DatetimeIndex*, *TimedeltaIndex*, *Index*, *Series*, or *DataFrame* (GH24486)
- *to_timedelta()*, *Timedelta*, and *TimedeltaIndex* no longer allow "M", "y", or "Y" for the "unit" argument (GH23264)
- Removed the previously deprecated keyword "time_rule" from (non-public) `offsets.generate_range`, which has been moved to `core.arrays._ranges.generate_range()` (GH24157)
- *DataFrame.loc()* or *Series.loc()* with listlike indexers and missing labels will no longer reindex (GH17295)
- *DataFrame.to_excel()* and *Series.to_excel()* with non-existent columns will no longer reindex (GH17295)
- Removed the previously deprecated keyword "join_axes" from *concat()*; use `reindex_like` on the result instead (GH22318)
- Removed the previously deprecated keyword "by" from *DataFrame.sort_index()*, use *DataFrame.sort_values()* instead (GH10726)
- Removed support for nested renaming in *DataFrame.aggregate()*, *Series.aggregate()*, *core.groupby.DataFrameGroupBy.aggregate()*, *core.groupby.SeriesGroupBy.aggregate()*, *core.window.rolling.Rolling.aggregate()* (GH18529)
- Passing `datetime64` data to *TimedeltaIndex* or `timedelta64` data to `DatetimeIndex` now raises `TypeError` (GH23539, GH23937)
- Passing `int64` values to *DatetimeIndex* and a timezone now interprets the values as nanosecond timestamps in UTC, not wall times in the given timezone (GH24559)
- A tuple passed to *DataFrame.groupby()* is now exclusively treated as a single key (GH18314)
- Removed `Index.contains`, use `key in index` instead (GH30103)
- Addition and subtraction of `int` or integer-arrays is no longer allowed in *Timestamp*, *DatetimeIndex*, *TimedeltaIndex*, use `obj + n * obj.freq` instead of `obj + n` (GH22535)
- Removed `Series.ptp` (GH21614)
- Removed `Series.from_array` (GH18258)
- Removed `DataFrame.from_items` (GH18458)
- Removed `DataFrame.as_matrix`, `Series.as_matrix` (GH18458)

- Removed `Series.asobject` (GH18477)
- Removed `DataFrame.as_blocks`, `Series.as_blocks`, `DataFrame.blocks`, `Series.blocks` (GH17656)
- *pandas.Series.str.cat()* now defaults to aligning `others`, using `join='left'` (GH27611)
- *pandas.Series.str.cat()* does not accept list-likes *within* list-likes anymore (GH27611)
- *Series.where()* with `Categorical` dtype (or *DataFrame.where()* with `Categorical` column) no longer allows setting new categories (GH24114)
- Removed the previously deprecated keywords "start", "end", and "periods" from the *DatetimeIndex*, *TimedeltaIndex*, and *PeriodIndex* constructors; use *date_range()*, *timedelta_range()*, and *period_range()* instead (GH23919)
- Removed the previously deprecated keyword "verify_integrity" from the *DatetimeIndex* and *TimedeltaIndex* constructors (GH23919)
- Removed the previously deprecated keyword "fastpath" from `pandas.core.internals.blocks.make_block` (GH19265)
- Removed the previously deprecated keyword "dtype" from `Block.make_block_same_class()` (GH19434)
- Removed `ExtensionArray._formatting_values`. Use `ExtensionArray._formatter` instead. (GH23601)
- Removed `MultiIndex.to_hierarchical` (GH21613)
- Removed `MultiIndex.labels`, use *MultiIndex.codes* instead (GH23752)
- Removed the previously deprecated keyword "labels" from the *MultiIndex* constructor, use "codes" instead (GH23752)
- Removed `MultiIndex.set_labels`, use *MultiIndex.set_codes()* instead (GH23752)
- Removed the previously deprecated keyword "labels" from *MultiIndex.set_codes()*, `MultiIndex.copy()`, `MultiIndex.drop()`, use "codes" instead (GH23752)
- Removed support for legacy HDF5 formats (GH29787)
- Passing a dtype alias (e.g. 'datetime64[ns, UTC]') to *DatetimeTZDtype* is no longer allowed, use `DatetimeTZDtype.construct_from_string()` instead (GH23990)
- Removed the previously deprecated keyword "skip_footer" from *read_excel()*; use "skipfooter" instead (GH18836)
- *read_excel()* no longer allows an integer value for the parameter `usecols`, instead pass a list of integers from 0 to `usecols` inclusive (GH23635)
- Removed the previously deprecated keyword "convert_datetime64" from *DataFrame.to_records()* (GH18902)
- Removed `IntervalIndex.from_intervals` in favor of the *IntervalIndex* constructor (GH19263)
- Changed the default "keep_tz" argument in *DatetimeIndex.to_series()* from `None` to `True` (GH23739)
- Removed `api.types.is_period` and `api.types.is_datetimetz` (GH23917)
- Ability to read pickles containing *Categorical* instances created with pre-0.16 version of pandas has been removed (GH27538)
- Removed `pandas.tseries.plotting.tsplot` (GH18627)

- Removed the previously deprecated keywords "reduce" and "broadcast" from *DataFrame.apply()* (GH18577)
- Removed the previously deprecated `assert_raises_regex` function in `pandas._testing` (GH29174)
- Removed the previously deprecated `FrozenNDArray` class in `pandas.core.indexes.frozen` (GH29335)
- Removed the previously deprecated keyword "nthreads" from *read_feather()*, use "use_threads" instead (GH23053)
- Removed `Index.is_lexsorted_for_tuple` (GH29305)
- Removed support for nested renaming in *DataFrame.aggregate()*, *Series.aggregate()*, *core.groupby.DataFrameGroupBy.aggregate()*, *core.groupby.SeriesGroupBy.aggregate()*, *core.window.rolling.Rolling.aggregate()* (GH29608)
- Removed `Series.valid`; use *Series.dropna()* instead (GH18800)
- Removed `DataFrame.is_copy`, `Series.is_copy` (GH18812)
- Removed `DataFrame.get_ftype_counts`, `Series.get_ftype_counts` (GH18243)
- Removed `DataFrame.ftypes`, `Series.ftypes`, `Series.ftype` (GH26744)
- Removed `Index.get_duplicates`, use `idx[idx.duplicated()].unique()` instead (GH20239)
- Removed `Series.clip_upper`, `Series.clip_lower`, `DataFrame.clip_upper`, `DataFrame.clip_lower` (GH24203)
- Removed the ability to alter *DatetimeIndex.freq*, `TimedeltaIndex.freq`, or *PeriodIndex.freq* (GH20772)
- Removed `DatetimeIndex.offset` (GH20730)
- Removed `DatetimeIndex.asobject`, `TimedeltaIndex.asobject`, `PeriodIndex.asobject`, use `astype(object)` instead (GH29801)
- Removed the previously deprecated keyword "order" from *factorize()* (GH19751)
- Removed the previously deprecated keyword "encoding" from *read_stata()* and *DataFrame.to_stata()* (GH21400)
- Changed the default "sort" argument in *concat()* from `None` to `False` (GH20613)
- Removed the previously deprecated keyword "raise_conflict" from *DataFrame.update()*, use "errors" instead (GH23585)
- Removed the previously deprecated keyword "n" from `DatetimeIndex.shift()`, `TimedeltaIndex.shift()`, `PeriodIndex.shift()`, use "periods" instead (GH22458)
- Removed the previously deprecated keywords "how", "fill_method", and "limit" from *DataFrame.resample()* (GH30139)
- Passing an integer to *Series.fillna()* or *DataFrame.fillna()* with `timedelta64[ns]` dtype now raises `TypeError` (GH24694)
- Passing multiple axes to *DataFrame.dropna()* is no longer supported (GH20995)
- Removed `Series.nonzero`, use `to_numpy().nonzero()` instead (GH24048)
- Passing floating dtype `codes` to *Categorical.from_codes()* is no longer supported, pass `codes.astype(np.int64)` instead (GH21775)
- Removed the previously deprecated keyword "pat" from *Series.str.partition()* and *Series.str.rpartition()*, use "sep" instead (GH23767)

- Removed `Series.put` (GH27106)
- Removed `Series.real`, `Series.imag` (GH27106)
- Removed `Series.to_dense`, `DataFrame.to_dense` (GH26684)
- Removed `Index.dtype_str`, use `str(index.dtype)` instead (GH27106)
- `Categorical.ravel()` returns a *Categorical* instead of a `ndarray` (GH27199)
- The 'outer' method on Numpy ufuncs, e.g. `np.subtract.outer` operating on *Series* objects is no longer supported, and will raise `NotImplementedError` (GH27198)
- Removed `Series.get_dtype_counts` and `DataFrame.get_dtype_counts` (GH27145)
- Changed the default "fill_value" argument in `Categorical.take()` from `True` to `False` (GH20841)
- Changed the default value for the `raw` argument in `Series.rolling().apply()`, `DataFrame.rolling().apply()`, `Series.expanding().apply()`, and `DataFrame.expanding().apply()` from `None` to `False` (GH20584)
- Removed deprecated behavior of *Series.argmin()* and *Series.argmax()*, use *Series.idxmin()* and *Series.idxmax()* for the old behavior (GH16955)
- Passing a tz-aware `datetime.datetime` or *Timestamp* into the *Timestamp* constructor with the `tz` argument now raises a `ValueError` (GH23621)
- Removed `Series.base`, `Index.base`, `Categorical.base`, `Series.flags`, `Index.flags`, `PeriodArray.flags`, `Series.strides`, `Index.strides`, `Series.itemsize`, `Index.itemsize`, `Series.data`, `Index.data` (GH20721)
- Changed *Timedelta.resolution()* to match the behavior of the standard library `datetime.timedelta.resolution`, for the old behavior, use *Timedelta.resolution_string()* (GH26839)
- Removed `Timestamp.weekday_name`, `DatetimeIndex.weekday_name`, and `Series.dt.weekday_name` (GH18164)
- Removed the previously deprecated keyword "errors" in *Timestamp.tz_localize()*, *DatetimeIndex.tz_localize()*, and *Series.tz_localize()* (GH22644)
- Changed the default "ordered" argument in *CategoricalDtype* from `None` to `False` (GH26336)
- *Series.set_axis()* and *DataFrame.set_axis()* now require "labels" as the first argument and "axis" as an optional named parameter (GH30089)
- Removed `to_msgpack`, `read_msgpack`, `DataFrame.to_msgpack`, `Series.to_msgpack` (GH27103)
- Removed `Series.compress` (GH21930)
- Removed the previously deprecated keyword "fill_value" from `Categorical.fillna()`, use "value" instead (GH19269)
- Removed the previously deprecated keyword "data" from `andrews_curves()`, use "frame" instead (GH6956)
- Removed the previously deprecated keyword "data" from `parallel_coordinates()`, use "frame" instead (GH6956)
- Removed the previously deprecated keyword "colors" from `parallel_coordinates()`, use "color" instead (GH6956)
- Removed the previously deprecated keywords "verbose" and "private_key" from *read_gbq()* (GH30200)
- Calling `np.array` and `np.asarray` on tz-aware *Series* and *DatetimeIndex* will now return an object array of tz-aware *Timestamp* (GH24596)

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Performance improvements

- Performance improvement in *DataFrame* arithmetic and comparison operations with scalars (GH24990, GH29853)
- Performance improvement in indexing with a non-unique *IntervalIndex* (GH27489)
- Performance improvement in `MultiIndex.is_monotonic` (GH27495)
- Performance improvement in *cut()* when `bins` is an *IntervalIndex* (GH27668)
- Performance improvement when initializing a *DataFrame* using a `range` (GH30171)
- Performance improvement in *DataFrame.corr()* when `method` is `"spearman"` (GH28139)
- Performance improvement in *DataFrame.replace()* when provided a list of values to replace (GH28099)
- Performance improvement in *DataFrame.select_dtypes()* by using vectorization instead of iterating over a loop (GH28317)
- Performance improvement in `Categorical.searchsorted()` and `CategoricalIndex.searchsorted()` (GH28795)
- Performance improvement when comparing a *Categorical* with a scalar and the scalar is not found in the categories (GH29750)
- Performance improvement when checking if values in a *Categorical* are equal, equal or larger or larger than a given scalar. The improvement is not present if checking if the *Categorical* is less than or less than or equal than the scalar (GH29820)
- Performance improvement in *Index.equals()* and `MultiIndex.equals()` (GH29134)
- Performance improvement in *infer_dtype()* when `skipna` is `True` (GH28814)

Bug fixes

Categorical

- Added test to assert the `fillna()` raises the correct `ValueError` message when the value isn't a value from categories (GH13628)
- Bug in `Categorical.astype()` where `NaN` values were handled incorrectly when casting to int (GH28406)
- *DataFrame.reindex()* with a *CategoricalIndex* would fail when the targets contained duplicates, and wouldn't fail if the source contained duplicates (GH28107)
- Bug in `Categorical.astype()` not allowing for casting to extension dtypes (GH28668)
- Bug where *merge()* was unable to join on categorical and extension dtype columns (GH28668)
- `Categorical.searchsorted()` and `CategoricalIndex.searchsorted()` now work on unordered categoricals also (GH21667)
- Added test to assert roundtripping to parquet with *DataFrame.to_parquet()* or *read_parquet()* will preserve Categorical dtypes for string types (GH27955)
- Changed the error message in `Categorical.remove_categories()` to always show the invalid removals as a set (GH28669)

- Using date accessors on a categorical dtyped *Series* of datetimes was not returning an object of the same type as if one used the `str.()` / `dt.()` on a *Series* of that type. E.g. when accessing *Series.dt.tz_localize()* on a *Categorical* with duplicate entries, the accessor was skipping duplicates (GH27952)
- Bug in *DataFrame.replace()* and *Series.replace()* that would give incorrect results on categorical data (GH26988)
- Bug where calling `Categorical.min()` or `Categorical.max()` on an empty Categorical would raise a numpy exception (GH30227)
- The following methods now also correctly output values for unobserved categories when called through `groupby(..., observed=False)` (GH17605) * `core.groupby.SeriesGroupBy.count()` * `core.groupby.SeriesGroupBy.size()` * *core.groupby.SeriesGroupBy.nunique()* * `core.groupby.SeriesGroupBy.nth()`

Datetimelike

- Bug in `Series.__setitem__()` incorrectly casting `np.timedelta64("NaT")` to `np.datetime64("NaT")` when inserting into a *Series* with datetime64 dtype (GH27311)
- Bug in *Series.dt()* property lookups when the underlying data is read-only (GH27529)
- Bug in `HDFStore.__getitem__` incorrectly reading tz attribute created in Python 2 (GH26443)
- Bug in *to_datetime()* where passing arrays of malformed `str` with errors="coerce" could incorrectly lead to raising `ValueError` (GH28299)
- Bug in *core.groupby.SeriesGroupBy.nunique()* where `NaT` values were interfering with the count of unique values (GH27951)
- Bug in *Timestamp* subtraction when subtracting a *Timestamp* from a `np.datetime64` object incorrectly raising `TypeError` (GH28286)
- Addition and subtraction of integer or integer-dtype arrays with *Timestamp* will now raise `NullFrequencyError` instead of `ValueError` (GH28268)
- Bug in *Series* and *DataFrame* with integer dtype failing to raise `TypeError` when adding or subtracting a `np.datetime64` object (GH28080)
- Bug in *Series.astype()*, *Index.astype()*, and *DataFrame.astype()* failing to handle `NaT` when casting to an integer dtype (GH28492)
- Bug in `Week` with `weekday` incorrectly raising `AttributeError` instead of `TypeError` when adding or subtracting an invalid type (GH28530)
- Bug in *DataFrame* arithmetic operations when operating with a *Series* with dtype `'timedelta64[ns]'` (GH28049)
- Bug in `core.groupby.generic.SeriesGroupBy.apply()` raising `ValueError` when a column in the original DataFrame is a datetime and the column labels are not standard integers (GH28247)
- Bug in `pandas._config.localization.get_locales()` where the `locales -a` encodes the locales list as windows-1252 (GH23638, GH24760, GH27368)
- Bug in *Series.var()* failing to raise `TypeError` when called with `timedelta64[ns]` dtype (GH28289)
- Bug in *DatetimeIndex.strftime()* and *Series.dt.strftime()* where `NaT` was converted to the string `'NaT'` instead of `np.nan` (GH29578)

- Bug in masking datetime-like arrays with a boolean mask of an incorrect length not raising an `IndexError` (GH30308)
- Bug in *`Timestamp.resolution`* being a property instead of a class attribute (GH29910)
- Bug in *`pandas.to_datetime()`* when called with `None` raising `TypeError` instead of returning `NaT` (GH30011)
- Bug in *`pandas.to_datetime()`* failing for `deques` when using `cache=True` (the default) (GH29403)
- Bug in *`Series.item()`* with `datetime64` or `timedelta64` dtype, `DatetimeIndex.item()`, and `TimedeltaIndex.item()` returning an integer instead of a *`Timestamp`* or *`Timedelta`* (GH30175)
- Bug in *`DatetimeIndex`* addition when adding a non-optimized `DateOffset` incorrectly dropping timezone information (GH30336)
- Bug in *`DataFrame.drop()`* where attempting to drop non-existent values from a DatetimeIndex would yield a confusing error message (GH30399)
- Bug in *`DataFrame.append()`* would remove the timezone-awareness of new data (GH30238)
- Bug in *`Series.cummin()`* and *`Series.cummax()`* with timezone-aware dtype incorrectly dropping its timezone (GH15553)
- Bug in `DatetimeArray`, `TimedeltaArray`, and `PeriodArray` where inplace addition and subtraction did not actually operate inplace (GH24115)
- Bug in *`pandas.to_datetime()`* when called with `Series` storing `IntegerArray` raising `TypeError` instead of returning `Series` (GH30050)
- Bug in *`date_range()`* with custom business hours as `freq` and given number of `periods` (GH30593)
- Bug in *`PeriodIndex`* comparisons with incorrectly casting integers to *`Period`* objects, inconsistent with the *`Period`* comparison behavior (GH30722)
- Bug in `DatetimeIndex.insert()` raising a `ValueError` instead of a `TypeError` when trying to insert a timezone-aware *`Timestamp`* into a timezone-naive *`DatetimeIndex`*, or vice-versa (GH30806)

Timedelta

- Bug in subtracting a *`TimedeltaIndex`* or `TimedeltaArray` from a `np.datetime64` object (GH29558)
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Timezones

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Numeric

- Bug in *`DataFrame.quantile()`* with zero-column *`DataFrame`* incorrectly raising (GH23925)
- *`DataFrame`* flex inequality comparisons methods (*`DataFrame.lt()`*, *`DataFrame.le()`*, *`DataFrame.gt()`*, *`DataFrame.ge()`*) with object-dtype and `complex` entries failing to raise `TypeError` like their *`Series`* counterparts (GH28079)
- Bug in *`DataFrame`* logical operations (`&`, `|`, `^`) not matching *`Series`* behavior by filling NA values (GH28741)

- Bug in *DataFrame.interpolate()* where specifying axis by name references variable before it is assigned (GH29142)
- Bug in *Series.var()* not computing the right value with a nullable integer dtype series not passing through ddof argument (GH29128)
- Improved error message when using `frac` > 1 and `replace` = False (GH27451)
- Bug in numeric indexes resulted in it being possible to instantiate an *Int64Index*, *UInt64Index*, or *Float64Index* with an invalid dtype (e.g. datetime-like) (GH29539)
- Bug in *UInt64Index* precision loss while constructing from a list with values in the `np.uint64` range (GH29526)
- Bug in `NumericIndex` construction that caused indexing to fail when integers in the `np.uint64` range were used (GH28023)
- Bug in `NumericIndex` construction that caused *UInt64Index* to be casted to *Float64Index* when integers in the `np.uint64` range were used to index a *DataFrame* (GH28279)
- Bug in *Series.interpolate()* when using method=`index` with an unsorted index, would previously return incorrect results. (GH21037)
- Bug in *DataFrame.round()* where a *DataFrame* with a *CategoricalIndex* of *IntervalIndex* columns would incorrectly raise a `TypeError` (GH30063)
- Bug in *Series.pct_change()* and *DataFrame.pct_change()* when there are duplicated indices (GH30463)
- Bug in *DataFrame* cumulative operations (e.g. cumsum, cummax) incorrect casting to object-dtype (GH19296)
- Bug in *diff* losing the dtype for extension types (GH30889)
- Bug in *DataFrame.diff* raising an `IndexError` when one of the columns was a nullable integer dtype (GH30967)

Conversion

-

Strings

- Calling *Series.str.isalnum()* (and other "ismethods") on an empty `Series` would return an `object` dtype instead of `bool` (GH29624)
-

Interval

- Bug in *IntervalIndex.get_indexer()* where a *Categorical* or *CategoricalIndex* `target` would incorrectly raise a `TypeError` (GH30063)
- Bug in `pandas.core.dtypes.cast.infer_dtype_from_scalar` where passing `pandas_dtype=True` did not infer *IntervalDtype* (GH30337)
- Bug in *Series* constructor where constructing a `Series` from a `list` of *Interval* objects resulted in `object` dtype instead of *IntervalDtype* (GH23563)

- Bug in *IntervalDtype* where the `kind` attribute was incorrectly set as `None` instead of `"O"` (GH30568)
- Bug in *IntervalIndex*, *IntervalArray*, and *Series* with interval data where equality comparisons were incorrect (GH24112)

Indexing

- Bug in assignment using a reverse slicer (GH26939)
- Bug in *DataFrame.explode()* would duplicate frame in the presence of duplicates in the index (GH28010)
- Bug in reindexing a *PeriodIndex()* with another type of index that contained a `Period` (GH28323) (GH28337)
- Fix assignment of column via `.loc` with numpy non-ns datetime type (GH27395)
- Bug in `Float64Index.astype()` where `np.inf` was not handled properly when casting to an integer dtype (GH28475)
- *Index.union()* could fail when the left contained duplicates (GH28257)
- Bug when indexing with `.loc` where the index was a *CategoricalIndex* with non-string categories didn't work (GH17569, GH30225)
- *Index.get_indexer_non_unique()* could fail with `TypeError` in some cases, such as when searching for ints in a string index (GH28257)
- Bug in `Float64Index.get_loc()` incorrectly raising `TypeError` instead of `KeyError` (GH29189)
- Bug in *DataFrame.loc()* with incorrect dtype when setting Categorical value in 1-row DataFrame (GH25495)
- *MultiIndex.get_loc()* can't find missing values when input includes missing values (GH19132)
- Bug in `Series.__setitem__()` incorrectly assigning values with boolean indexer when the length of new data matches the number of `True` values and new data is not a `Series` or an `np.array` (GH30567)
- Bug in indexing with a *PeriodIndex* incorrectly accepting integers representing years, use e.g. `ser.loc["2007"]` instead of `ser.loc[2007]` (GH30763)

Missing

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MultiIndex

- Constructor for *MultiIndex* verifies that the given `sortorder` is compatible with the actual `lexsort_depth` if `verify_integrity` parameter is `True` (the default) (GH28735)
- Series and MultiIndex `.drop` with `MultiIndex` raise exception if labels not in given in level (GH8594)
-

IO

- *read_csv()* now accepts binary mode file buffers when using the Python csv engine (GH23779)
- Bug in *DataFrame.to_json()* where using a Tuple as a column or index value and using `orient="columns"` or `orient="index"` would produce invalid JSON (GH20500)
- Improve infinity parsing. *read_csv()* now interprets `Infinity`, `+Infinity`, `-Infinity` as floating point values (GH10065)
- Bug in *DataFrame.to_csv()* where values were truncated when the length of `na_rep` was shorter than the text input data. (GH25099)
- Bug in *DataFrame.to_string()* where values were truncated using display options instead of outputting the full content (GH9784)
- Bug in *DataFrame.to_json()* where a datetime column label would not be written out in ISO format with `orient="table"` (GH28130)
- Bug in *DataFrame.to_parquet()* where writing to GCS would fail with `engine='fastparquet'` if the file did not already exist (GH28326)
- Bug in *read_hdf()* closing stores that it didn't open when Exceptions are raised (GH28699)
- Bug in `DataFrame.read_json()` where using `orient="index"` would not maintain the order (GH28557)
- Bug in *DataFrame.to_html()* where the length of the `formatters` argument was not verified (GH28469)
- Bug in `DataFrame.read_excel()` with `engine='ods'` when `sheet_name` argument references a non-existent sheet (GH27676)
- Bug in *pandas.io.formats.style.Styler()* formatting for floating values not displaying decimals correctly (GH13257)
- Bug in *DataFrame.to_html()* when using `formatters=<list>` and `max_cols` together. (GH25955)
- Bug in `Styler.background_gradient()` not able to work with dtype `Int64` (GH28869)
- Bug in *DataFrame.to_clipboard()* which did not work reliably in ipython (GH22707)
- Bug in *read_json()* where default encoding was not set to `utf-8` (GH29565)
- Bug in `PythonParser` where str and bytes were being mixed when dealing with the decimal field (GH29650)
- *read_gbq()* now accepts `progress_bar_type` to display progress bar while the data downloads. (GH29857)
- Bug in `pandas.io.json.json_normalize()` where a missing value in the location specified by `record_path` would raise a `TypeError` (GH30148)
- *read_excel()* now accepts binary data (GH15914)
- Bug in *read_csv()* in which encoding handling was limited to just the string `utf-16` for the C engine (GH24130)

Plotting

- Bug in *Series.plot()* not able to plot boolean values (GH23719)
- Bug in *DataFrame.plot()* not able to plot when no rows (GH27758)
- Bug in *DataFrame.plot()* producing incorrect legend markers when plotting multiple series on the same axis (GH18222)
- Bug in *DataFrame.plot()* when `kind='box'` and data contains datetime or timedelta data. These types are now automatically dropped (GH22799)
- Bug in *DataFrame.plot.line()* and *DataFrame.plot.area()* produce wrong xlim in x-axis (GH27686, GH25160, GH24784)
- Bug where *DataFrame.boxplot()* would not accept a `color` parameter like *DataFrame.plot.box()* (GH26214)
- Bug in the `xticks` argument being ignored for *DataFrame.plot.bar()* (GH14119)
- *set_option()* now validates that the plot backend provided to `'plotting.backend'` implements the backend when the option is set, rather than when a plot is created (GH28163)
- *DataFrame.plot()* now allow a `backend` keyword argument to allow changing between backends in one session (GH28619).
- Bug in color validation incorrectly raising for non-color styles (GH29122).
- Allow *DataFrame.plot.scatter()* to plot `objects` and `datetime` type data (GH18755, GH30391)
- Bug in *DataFrame.hist()*, `xrot=0` does not work with `by` and subplots (GH30288).

GroupBy/resample/rolling

- Bug in `core.groupby.DataFrameGroupBy.apply()` only showing output from a single group when function returns an *Index* (GH28652)
- Bug in *DataFrame.groupby()* with multiple groups where an `IndexError` would be raised if any group contained all NA values (GH20519)
- Bug in *pandas.core.resample.Resampler.size()* and *pandas.core.resample.Resampler.count()* returning wrong dtype when used with an empty *Series* or *DataFrame* (GH28427)
- Bug in *DataFrame.rolling()* not allowing for rolling over datetimes when `axis=1` (GH28192)
- Bug in *DataFrame.rolling()* not allowing rolling over multi-index levels (GH15584).
- Bug in *DataFrame.rolling()* not allowing rolling on monotonic decreasing time indexes (GH19248).
- Bug in *DataFrame.groupby()* not offering selection by column name when `axis=1` (GH27614)
- Bug in `core.groupby.DataFrameGroupby.agg()` not able to use lambda function with named aggregation (GH27519)
- Bug in *DataFrame.groupby()* losing column name information when grouping by a categorical column (GH28787)
- Remove error raised due to duplicated input functions in named aggregation in *DataFrame.groupby()* and *Series.groupby()*. Previously error will be raised if the same function is applied on the same column and now it is allowed if new assigned names are different. (GH28426)

- *core.groupby.SeriesGroupBy.value_counts()* will be able to handle the case even when the *Grouper* makes empty groups (GH28479)
- Bug in *core.window.rolling.Rolling.quantile()* ignoring `interpolation` keyword argument when used within a groupby (GH28779)
- Bug in *DataFrame.groupby()* where `any`, `all`, `nunique` and transform functions would incorrectly handle duplicate column labels (GH21668)
- Bug in `core.groupby.DataFrameGroupBy.agg()` with timezone-aware datetime64 column incorrectly casting results to the original dtype (GH29641)
- Bug in *DataFrame.groupby()* when using axis=1 and having a single level columns index (GH30208)
- Bug in *DataFrame.groupby()* when using nunique on axis=1 (GH30253)
- Bug in `GroupBy.quantile()` with multiple list-like q value and integer column names (GH30289)
- Bug in `GroupBy.pct_change()` and `core.groupby.SeriesGroupBy.pct_change()` causes `TypeError` when `fill_method` is `None` (GH30463)
- Bug in `Rolling.count()` and `Expanding.count()` argument where `min_periods` was ignored (GH26996)

Reshaping

- Bug in *DataFrame.apply()* that caused incorrect output with empty *DataFrame* (GH28202, GH21959)
- Bug in *DataFrame.stack()* not handling non-unique indexes correctly when creating MultiIndex (GH28301)
- Bug in *pivot_table()* not returning correct type `float` when `margins=True` and `aggfunc='mean'` (GH24893)
- Bug *merge_asof()* could not use `datetime.timedelta` for `tolerance` kwarg (GH28098)
- Bug in *merge()*, did not append suffixes correctly with MultiIndex (GH28518)
- *qcut()* and *cut()* now handle boolean input (GH20303)
- Fix to ensure all int dtypes can be used in *merge_asof()* when using a tolerance value. Previously every non-int64 type would raise an erroneous `MergeError` (GH28870).
- Better error message in *get_dummies()* when `columns` isn't a list-like value (GH28383)
- Bug in *Index.join()* that caused infinite recursion error for mismatched `MultiIndex` name orders. (GH25760, GH28956)
- Bug *Series.pct_change()* where supplying an anchored frequency would throw a `ValueError` (GH28664)
- Bug where *DataFrame.equals()* returned True incorrectly in some cases when two DataFrames had the same columns in different orders (GH28839)
- Bug in *DataFrame.replace()* that caused non-numeric replacer's dtype not respected (GH26632)
- Bug in *melt()* where supplying mixed strings and numeric values for `id_vars` or `value_vars` would incorrectly raise a `ValueError` (GH29718)
- Dtypes are now preserved when transposing a `DataFrame` where each column is the same extension dtype (GH30091)
- Bug in *merge_asof()* merging on a tz-aware `left_index` and `right_on` a tz-aware column (GH29864)

- Improved error message and docstring in *cut()* and *qcut()* when `labels=True` (GH13318)
- Bug in missing `fill_na` parameter to *DataFrame.unstack()* with list of levels (GH30740)

Sparse

- Bug in `SparseDataFrame` arithmetic operations incorrectly casting inputs to float (GH28107)
- Bug in `DataFrame.sparse` returning a `Series` when there was a column named `sparse` rather than the accessor (GH30758)
- Fixed `operator.xor()` with a boolean-dtype `SparseArray`. Now returns a sparse result, rather than object dtype (GH31025)

ExtensionArray

- Bug in *arrays.PandasArray* when setting a scalar string (GH28118, GH28150).
- Bug where nullable integers could not be compared to strings (GH28930)
- Bug where *DataFrame* constructor raised `ValueError` with list-like data and `dtype` specified (GH30280)

Other

- Trying to set the `display.precision`, `display.max_rows` or `display.max_columns` using *set_option()* to anything but a `None` or a positive int will raise a `ValueError` (GH23348)
- Using *DataFrame.replace()* with overlapping keys in a nested dictionary will no longer raise, now matching the behavior of a flat dictionary (GH27660)
- *DataFrame.to_csv()* and *Series.to_csv()* now support dicts as `compression` argument with key `'method'` being the compression method and others as additional compression options when the compression method is `'zip'`. (GH26023)
- Bug in *Series.diff()* where a boolean series would incorrectly raise a `TypeError` (GH17294)
- *Series.append()* will no longer raise a `TypeError` when passed a tuple of `Series` (GH28410)
- Fix corrupted error message when calling `pandas.libs._json.encode()` on a 0d array (GH18878)
- Backtick quoting in *DataFrame.query()* and *DataFrame.eval()* can now also be used to use invalid identifiers like names that start with a digit, are python keywords, or are using single character operators. (GH27017)
- Bug in `pd.core.util.hashing.hash_pandas_object` where arrays containing tuples were incorrectly treated as non-hashable (GH28969)
- Bug in *DataFrame.append()* that raised `IndexError` when appending with empty list (GH28769)
- Fix `AbstractHolidayCalendar` to return correct results for years after 2030 (now goes up to 2200) (GH27790)
- Fixed *IntegerArray* returning `inf` rather than `NaN` for operations dividing by `0` (GH27398)
- Fixed `pow` operations for *IntegerArray* when the other value is `0` or `1` (GH29997)
- Bug in *Series.count()* raises if use_inf_as_na is enabled (GH29478)
- Bug in *Index* where a non-hashable name could be set without raising `TypeError` (GH29069)

- Bug in *DataFrame* constructor when passing a 2D `ndarray` and an extension dtype (GH12513)
- Bug in *DataFrame.to_csv()* when supplied a series with a `dtype="string"` and a `na_rep`, the `na_rep` was being truncated to 2 characters. (GH29975)
- Bug where *DataFrame.itertuples()* would incorrectly determine whether or not namedtuples could be used for dataframes of 255 columns (GH28282)
- Handle nested NumPy `object` arrays in *testing.assert_series_equal()* for ExtensionArray implementations (GH30841)
- Bug in *Index* constructor incorrectly allowing 2-dimensional input arrays (GH13601, GH27125)

Contributors

A total of 308 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- h-vetinari
- hasnain2808 +
- ianzur +
- jalbritt +
- jbrockmendel
- jeschwar +
- jlamborn324 +
- joy-rosie +
- kernc
- killerontherun1
- krey +

- lexy-lixinyu +
- lucyleeow +
- lukasbk +
- maheshbapatu +
- mck619 +
- nathalier
- naveenkaushik2504 +
- nlepleux +
- nrebena
- ohad83 +
- pilkibun
- pqzx +
- proost +
- pv8493013j +
- qudade +
- rhstanton +
- rmunjal29 +
- sangarshanan +
- sardonick +
- saskakarsi +
- shaido987 +
- ssikdar1
- steveayers124 +
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5.4 Version 0.25

5.4.1 What's new in 0.25.3 (October 31, 2019)

These are the changes in pandas 0.25.3. See *Release notes* for a full changelog including other versions of pandas.

Bug fixes

GroupBy/resample/rolling

- Bug in `DataFrameGroupBy.quantile()` where NA values in the grouping could cause segfaults or incorrect results (GH28882)

Contributors

A total of 2 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Will Ayd
- William Ayd

5.4.2 What's new in 0.25.2 (October 15, 2019)

These are the changes in pandas 0.25.2. See *Release notes* for a full changelog including other versions of pandas.

Note: pandas 0.25.2 adds compatibility for Python 3.8 (GH28147).

Bug fixes

Indexing

- Fix regression in `DataFrame.reindex()` not following the `limit` argument (GH28631).
- Fix regression in `RangeIndex.get_indexer()` for decreasing `RangeIndex` where target values may be improperly identified as missing/present (GH28678)

IO

- Fix regression in notebook display where `<th>` tags were missing for `DataFrame.index` values (GH28204).
- Regression in `to_csv()` where writing a `Series` or `DataFrame` indexed by an `IntervalIndex` would incorrectly raise a `TypeError` (GH28210)
- Fix `to_csv()` with `ExtensionArray` with list-like values (GH28840).

GroupBy/resample/rolling

- Bug incorrectly raising an `IndexError` when passing a list of quantiles to *pandas.core.groupby.DataFrameGroupBy.quantile()* (GH28113).
- Bug in `pandas.core.groupby.GroupBy.shift()`, *pandas.core.groupby.GroupBy.bfill()* and *pandas.core.groupby.GroupBy.ffill()* where timezone information would be dropped (GH19995, GH27992)

Other

- Compatibility with Python 3.8 in `DataFrame.query()` (GH27261)
- Fix to ensure that tab-completion in an IPython console does not raise warnings for deprecated attributes (GH27900).

Contributors

A total of 6 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Felix Divo +
- Jeremy Schendel
- Joris Van den Bossche
- MeeseeksMachine
- Tom Augspurger
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5.4.3 What's new in 0.25.1 (August 21, 2019)

These are the changes in pandas 0.25.1. See *Release notes* for a full changelog including other versions of pandas.

IO and LZMA

Some users may unknowingly have an incomplete Python installation lacking the `lzma` module from the standard library. In this case, `import pandas` failed due to an `ImportError` (GH27575). pandas will now warn, rather than raising an `ImportError` if the `lzma` module is not present. Any subsequent attempt to use `lzma` methods will raise a `RuntimeError`. A possible fix for the lack of the `lzma` module is to ensure you have the necessary libraries and then re-install Python. For example, on MacOS installing Python with `pyenv` may lead to an incomplete Python installation due to unmet system dependencies at compilation time (like `xz`). Compilation will succeed, but Python might fail at run time. The issue can be solved by installing the necessary dependencies and then re-installing Python.

Bug fixes

Categorical

- Bug in `Categorical.fillna()` that would replace all values, not just those that are `NaN` (GH26215)

Datetimelike

- Bug in `to_datetime()` where passing a timezone-naive `DatetimeArray` or `DatetimeIndex` and `utc=True` would incorrectly return a timezone-naive result (GH27733)
- Bug in `Period.to_timestamp()` where a `Period` outside the `Timestamp` implementation bounds (roughly 1677-09-21 to 2262-04-11) would return an incorrect `Timestamp` instead of raising `OutOfBoundsDatetime` (GH19643)
- Bug in iterating over `DatetimeIndex` when the underlying data is read-only (GH28055)

Timezones

- Bug in `Index` where a numpy object array with a timezone aware `Timestamp` and `np.nan` would not return a `DatetimeIndex` (GH27011)

Numeric

- Bug in `Series.interpolate()` when using a timezone aware `DatetimeIndex` (GH27548)
- Bug when printing negative floating point complex numbers would raise an `IndexError` (GH27484)
- Bug where `DataFrame` arithmetic operators such as `DataFrame.mul()` with a `Series` with axis=1 would raise an `AttributeError` on `DataFrame` larger than the minimum threshold to invoke numexpr (GH27636)
- Bug in `DataFrame` arithmetic where missing values in results were incorrectly masked with `NaN` instead of `Inf` (GH27464)

Conversion

- Improved the warnings for the deprecated methods `Series.real()` and `Series.imag()` (GH27610)

Interval

- Bug in `IntervalIndex` where `dir(obj)` would raise `ValueError` (GH27571)

Indexing

- Bug in partial-string indexing returning a NumPy array rather than a `Series` when indexing with a scalar like `.loc['2015']` (GH27516)
- Break reference cycle involving `Index` and other index classes to allow garbage collection of index objects without running the GC. (GH27585, GH27840)
- Fix regression in assigning values to a single column of a DataFrame with a `MultiIndex` columns (GH27841).
- Fix regression in `.ix` fallback with an `IntervalIndex` (GH27865).

Missing

- Bug in *pandas.isnull()* or *pandas.isna()* when the input is a type e.g. `type(pandas.Series())` (GH27482)

IO

- Avoid calling `S3File.s3` when reading parquet, as this was removed in s3fs version 0.3.0 (GH27756)
- Better error message when a negative header is passed in *pandas.read_csv()* (GH27779)
- Follow the `min_rows` display option (introduced in v0.25.0) correctly in the HTML repr in the notebook (GH27991).

Plotting

- Added a `pandas_plotting_backends` entrypoint group for registering plot backends. See *Plotting backends* for more (GH26747).
- Fixed the re-instatement of Matplotlib datetime converters after calling *pandas.plotting.deregister_matplotlib_converters()* (GH27481).
- Fix compatibility issue with matplotlib when passing a pandas `Index` to a plot call (GH27775).

GroupBy/resample/rolling

- Fixed regression in `pands.core.groupby.DataFrameGroupBy.quantile()` raising when multiple quantiles are given (GH27526)
- Bug in *pandas.core.groupby.DataFrameGroupBy.transform()* where applying a timezone conversion lambda function would drop timezone information (GH27496)
- Bug in *pandas.core.groupby.GroupBy.nth()* where `observed=False` was being ignored for Categorical groupers (GH26385)
- Bug in windowing over read-only arrays (GH27766)
- Fixed segfault in `pandas.core.groupby.DataFrameGroupBy.quantile` when an invalid quantile was passed (GH27470)

Reshaping

- A `KeyError` is now raised if `.unstack()` is called on a `Series` or `DataFrame` with a flat `Index` passing a name which is not the correct one (GH18303)
- Bug `merge_asof()` could not merge `Timedelta` objects when passing `tolerance` kwarg (GH27642)
- Bug in `DataFrame.crosstab()` when `margins` set to `True` and `normalize` is not `False`, an error is raised. (GH27500)
- `DataFrame.join()` now suppresses the `FutureWarning` when the sort parameter is specified (GH21952)
- Bug in `DataFrame.join()` raising with readonly arrays (GH27943)

Sparse

- Bug in reductions for `Series` with Sparse dtypes (GH27080)

Other

- Bug in `Series.replace()` and `DataFrame.replace()` when replacing timezone-aware timestamps using a dict-like replacer (GH27720)
- Bug in `Series.rename()` when using a custom type indexer. Now any value that isn't callable or dict-like is treated as a scalar. (GH27814)

Contributors

A total of 5 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Jeff Reback
- Joris Van den Bossche
- MeeseeksMachine +
- Tom Augspurger
- jbrockmendel

5.4.4 What's new in 0.25.0 (July 18, 2019)

Warning: Starting with the 0.25.x series of releases, pandas only supports Python 3.5.3 and higher. See Dropping Python 2.7 for more details.

Warning: The minimum supported Python version will be bumped to 3.6 in a future release.

Warning: `Panel` has been fully removed. For N-D labeled data structures, please use xarray

Warning: `read_pickle()` and `read_msgpack()` are only guaranteed backwards compatible back to pandas version 0.20.3 (GH27082)

These are the changes in pandas 0.25.0. See *Release notes* for a full changelog including other versions of pandas.

Enhancements

GroupBy aggregation with relabeling

pandas has added special groupby behavior, known as "named aggregation", for naming the output columns when applying multiple aggregation functions to specific columns (GH18366, GH26512).

```
In [1]: animals = pd.DataFrame({'kind': ['cat', 'dog', 'cat', 'dog'],
   ...:                         'height': [9.1, 6.0, 9.5, 34.0],
   ...:                         'weight': [7.9, 7.5, 9.9, 198.0]})
   ...:

In [2]: animals
Out[2]:
  kind  height  weight
0  cat     9.1     7.9
1  dog     6.0     7.5
2  cat     9.5     9.9
3  dog    34.0   198.0

[4 rows x 3 columns]

In [3]: animals.groupby("kind").agg(
   ...:     min_height=pd.NamedAgg(column='height', aggfunc='min'),
   ...:     max_height=pd.NamedAgg(column='height', aggfunc='max'),
   ...:     average_weight=pd.NamedAgg(column='weight', aggfunc=np.mean),
   ...: )
   ...:
Out[3]:
      min_height  max_height  average_weight
kind
cat          9.1         9.5            8.90
dog          6.0        34.0          102.75

[2 rows x 3 columns]
```

Pass the desired columns names as the `**kwargs` to `.agg`. The values of `**kwargs` should be tuples where the first element is the column selection, and the second element is the aggregation function to apply. pandas provides the `pandas.NamedAgg` namedtuple to make it clearer what the arguments to the function are, but plain tuples are accepted as well.

```
In [4]: animals.groupby("kind").agg(
   ...:     min_height=('height', 'min'),
   ...:     max_height=('height', 'max'),
   ...:     average_weight=('weight', np.mean),
   ...: )
   ...:
Out[4]:
      min_height  max_height  average_weight
```

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```
kind
cat          9.1         9.5            8.90
dog          6.0        34.0          102.75

[2 rows x 3 columns]
```

Named aggregation is the recommended replacement for the deprecated "dict-of-dicts" approach to naming the output of column-specific aggregations (*Deprecate groupby.agg() with a dictionary when renaming*).

A similar approach is now available for Series groupby objects as well. Because there's no need for column selection, the values can just be the functions to apply

```
In [5]: animals.groupby("kind").height.agg(
   ...:     min_height="min",
   ...:     max_height="max",
   ...: )
   ...:
Out[5]:
      min_height  max_height
kind
cat          9.1         9.5
dog          6.0        34.0

[2 rows x 2 columns]
```

This type of aggregation is the recommended alternative to the deprecated behavior when passing a dict to a Series groupby aggregation (*Deprecate groupby.agg() with a dictionary when renaming*).

See *Named aggregation* for more.

GroupBy aggregation with multiple lambdas

You can now provide multiple lambda functions to a list-like aggregation in *pandas.core.groupby.GroupBy.agg* (GH26430).

```
In [6]: animals.groupby('kind').height.agg([
   ...:     lambda x: x.iloc[0], lambda x: x.iloc[-1]
   ...: ])
   ...:
Out[6]:
      <lambda_0>  <lambda_1>
kind
cat          9.1         9.5
dog          6.0        34.0

[2 rows x 2 columns]

In [7]: animals.groupby('kind').agg([
   ...:     lambda x: x.iloc[0] - x.iloc[1],
   ...:     lambda x: x.iloc[0] + x.iloc[1]
   ...: ])
   ...:
Out[7]:
         height                  weight
     <lambda_0> <lambda_1> <lambda_0> <lambda_1>
```

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```
kind
cat        -0.4       18.6       -2.0       17.8
dog       -28.0       40.0     -190.5      205.5

[2 rows x 4 columns]
```

Previously, these raised a `SpecificationError`.

Better repr for MultiIndex

Printing of *MultiIndex* instances now shows tuples of each row and ensures that the tuple items are vertically aligned, so it's now easier to understand the structure of the `MultiIndex`. (GH13480):

The repr now looks like this:

```
In [8]: pd.MultiIndex.from_product([['a', 'abc'], range(500)])
Out[8]:
MultiIndex([(  'a',   0),
            (  'a',   1),
            (  'a',   2),
            (  'a',   3),
            (  'a',   4),
            (  'a',   5),
            (  'a',   6),
            (  'a',   7),
            (  'a',   8),
            (  'a',   9),
            ...
            ('abc', 490),
            ('abc', 491),
            ('abc', 492),
            ('abc', 493),
            ('abc', 494),
            ('abc', 495),
            ('abc', 496),
            ('abc', 497),
            ('abc', 498),
            ('abc', 499)],
           length=1000)
```

Previously, outputting a *MultiIndex* printed all the `levels` and `codes` of the `MultiIndex`, which was visually unappealing and made the output more difficult to navigate. For example (limiting the range to 5):

```
In [1]: pd.MultiIndex.from_product([['a', 'abc'], range(5)])
Out[1]: MultiIndex(levels=[['a', 'abc'], [0, 1, 2, 3]],
   ...:            codes=[[0, 0, 0, 0, 1, 1, 1, 1], [0, 1, 2, 3, 0, 1, 2, 3]])
```

In the new repr, all values will be shown, if the number of rows is smaller than `options.display.max_seq_items` (default: 100 items). Horizontally, the output will truncate, if it's wider than `options.display.width` (default: 80 characters).

Shorter truncated repr for Series and DataFrame

Currently, the default display options of pandas ensure that when a Series or DataFrame has more than 60 rows, its repr gets truncated to this maximum of 60 rows (the `display.max_rows` option). However, this still gives a repr that takes up a large part of the vertical screen estate. Therefore, a new option `display.min_rows` is introduced with a default of 10 which determines the number of rows showed in the truncated repr:

- For small Series or DataFrames, up to `max_rows` number of rows is shown (default: 60).
- For larger Series of DataFrame with a length above `max_rows`, only `min_rows` number of rows is shown (default: 10, i.e. the first and last 5 rows).

This dual option allows to still see the full content of relatively small objects (e.g. `df.head(20)` shows all 20 rows), while giving a brief repr for large objects.

To restore the previous behaviour of a single threshold, set `pd.options.display.min_rows = None`.

JSON normalize with max_level param support

`json_normalize()` normalizes the provided input dict to all nested levels. The new max_level parameter provides more control over which level to end normalization (GH23843):

The repr now looks like this:

```
from pandas.io.json import json_normalize
data = [{
    'CreatedBy': {'Name': 'User001'},
    'Lookup': {'TextField': 'Some text',
               'UserField': {'Id': 'ID001', 'Name': 'Name001'}},
    'Image': {'a': 'b'}
}]
json_normalize(data, max_level=1)
```

Series.explode to split list-like values to rows

`Series` and *`DataFrame`* have gained the *`DataFrame.explode()`* methods to transform list-likes to individual rows. See *section on Exploding list-like column* in docs for more information (GH16538, GH10511)

Here is a typical usecase. You have comma separated string in a column.

```
In [9]: df = pd.DataFrame([{'var1': 'a,b,c', 'var2': 1},
   ...:                    {'var1': 'd,e,f', 'var2': 2}])
   ...:

In [10]: df
Out[10]:
    var1  var2
0  a,b,c     1
1  d,e,f     2

[2 rows x 2 columns]
```

Creating a long form `DataFrame` is now straightforward using chained operations

```
In [11]: df.assign(var1=df.var1.str.split(',')).explode('var1')
Out[11]:
  var1  var2
0    a     1
0    b     1
0    c     1
1    d     2
1    e     2
1    f     2

[6 rows x 2 columns]
```

Other enhancements

- *DataFrame.plot()* keywords `logy`, `logx` and `loglog` can now accept the value `'sym'` for symlog scaling. (GH24867)
- Added support for ISO week year format ('%G-%V-%u') when parsing datetimes using *to_datetime()* (GH16607)
- Indexing of `DataFrame` and `Series` now accepts zerodim `np.ndarray` (GH24919)
- *Timestamp.replace()* now supports the `fold` argument to disambiguate DST transition times (GH25017)
- *DataFrame.at_time()* and *Series.at_time()* now support `datetime.time` objects with timezones (GH24043)
- *DataFrame.pivot_table()* now accepts an `observed` parameter which is passed to underlying calls to *DataFrame.groupby()* to speed up grouping categorical data. (GH24923)
- `Series.str` has gained *Series.str.casefold()* method to removes all case distinctions present in a string (GH25405)
- *DataFrame.set_index()* now works for instances of `abc.Iterator`, provided their output is of the same length as the calling frame (GH22484, GH24984)
- `DatetimeIndex.union()` now supports the `sort` argument. The behavior of the sort parameter matches that of *Index.union()* (GH24994)
- `RangeIndex.union()` now supports the `sort` argument. If `sort=False` an unsorted `Int64Index` is always returned. `sort=None` is the default and returns a monotonically increasing `RangeIndex` if possible or a sorted `Int64Index` if not (GH24471)
- `TimedeltaIndex.intersection()` now also supports the `sort` keyword (GH24471)
- *DataFrame.rename()* now supports the `errors` argument to raise errors when attempting to rename nonexistent keys (GH13473)
- Added *Sparse accessor* for working with a `DataFrame` whose values are sparse (GH25681)
- *RangeIndex* has gained *start*, *stop*, and *step* attributes (GH25710)
- `datetime.timezone` objects are now supported as arguments to timezone methods and constructors (GH25065)
- *DataFrame.query()* and *DataFrame.eval()* now supports quoting column names with backticks to refer to names with spaces (GH6508)
- *merge_asof()* now gives a more clear error message when merge keys are categoricals that are not equal (GH26136)

- `pandas.core.window.Rolling()` supports exponential (or Poisson) window type (GH21303)
- Error message for missing required imports now includes the original import error's text (GH23868)
- *`DatetimeIndex`* and *`TimedeltaIndex`* now have a `mean` method (GH24757)
- *`DataFrame.describe()`* now formats integer percentiles without decimal point (GH26660)
- Added support for reading SPSS .sav files using *`read_spss()`* (GH26537)
- Added new option `plotting.backend` to be able to select a plotting backend different than the existing `matplotlib` one. Use `pandas.set_option('plotting.backend', '<backend-module>')` where `<backend-module` is a library implementing the pandas plotting API (GH14130)
- `pandas.offsets.BusinessHour` supports multiple opening hours intervals (GH15481)
- *`read_excel()`* can now use `openpyxl` to read Excel files via the `engine='openpyxl'` argument. This will become the default in a future release (GH11499)
- `pandas.io.excel.read_excel()` supports reading OpenDocument tables. Specify `engine='odf'` to enable. Consult the *IO User Guide* for more details (GH9070)
- *`Interval`*, *`IntervalIndex`*, and *`IntervalArray`* have gained an *`is_empty`* attribute denoting if the given interval(s) are empty (GH27219)

Backwards incompatible API changes

Indexing with date strings with UTC offsets

Indexing a *`DataFrame`* or *`Series`* with a *`DatetimeIndex`* with a date string with a UTC offset would previously ignore the UTC offset. Now, the UTC offset is respected in indexing. (GH24076, GH16785)

```
In [12]: df = pd.DataFrame([0], index=pd.DatetimeIndex(['2019-01-01'], tz='US/Pacific
↪'))

In [13]: df
Out[13]:
                           0
2019-01-01 00:00:00-08:00  0

[1 rows x 1 columns]
```

Previous behavior:

```
In [3]: df['2019-01-01 00:00:00+04:00':'2019-01-01 01:00:00+04:00']
Out[3]:
                           0
2019-01-01 00:00:00-08:00  0
```

New behavior:

```
In [14]: df['2019-01-01 12:00:00+04:00':'2019-01-01 13:00:00+04:00']
Out[14]:
                           0
2019-01-01 00:00:00-08:00  0

[1 rows x 1 columns]
```

`MultiIndex` constructed from levels and codes

Constructing a *`MultiIndex`* with `NaN` levels or codes value < -1 was allowed previously. Now, construction with codes value < -1 is not allowed and `NaN` levels' corresponding codes would be reassigned as -1. (GH19387)

Previous behavior:

```
In [1]: pd.MultiIndex(levels=[[np.nan, None, pd.NaT, 128, 2]],
   ...:               codes=[[0, -1, 1, 2, 3, 4]])
   ...:
Out[1]: MultiIndex(levels=[[nan, None, NaT, 128, 2]],
                   codes=[[0, -1, 1, 2, 3, 4]])

In [2]: pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])
Out[2]: MultiIndex(levels=[[1, 2]],
                   codes=[[0, -2]])
```

New behavior:

```
In [15]: pd.MultiIndex(levels=[[np.nan, None, pd.NaT, 128, 2]],
   ....:               codes=[[0, -1, 1, 2, 3, 4]])
   ....:
Out[15]:
MultiIndex([(nan,),
            (nan,),
            (nan,),
            (nan,),
            (128,),
            (  2,)],
           )

In [16]: pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-16-225a01af3975> in <module>
----> 1 pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])

/pandas/pandas/core/indexes/multi.py in __new__(cls, levels, codes, sortorder, names,␣
↪dtype, copy, name, verify_integrity)
    314
    315         if verify_integrity:
--> 316             new_codes = result._verify_integrity()
    317             result._codes = new_codes
    318

/pandas/pandas/core/indexes/multi.py in _verify_integrity(self, codes, levels)
    387                 )
    388             if len(level_codes) and level_codes.min() < -1:
--> 389                 raise ValueError(f"On level {i}, code value ({level_codes.
↪min()}) < -1")
    390             if not level.is_unique:
    391                 raise ValueError(

ValueError: On level 0, code value (-2) < -1
```

`GroupBy.apply` on `DataFrame` evaluates first group only once

The implementation of `DataFrameGroupBy.apply()` previously evaluated the supplied function consistently twice on the first group to infer if it is safe to use a fast code path. Particularly for functions with side effects, this was an undesired behavior and may have led to surprises. (GH2936, GH2656, GH7739, GH10519, GH12155, GH20084, GH21417)

Now every group is evaluated only a single time.

```
In [17]: df = pd.DataFrame({"a": ["x", "y"], "b": [1, 2]})

In [18]: df
Out[18]:
   a  b
0  x  1
1  y  2

[2 rows x 2 columns]

In [19]: def func(group):
   ....:     print(group.name)
   ....:     return group
   ....:
```

Previous behavior:

```
In [3]: df.groupby('a').apply(func)
x
x
y
Out[3]:
   a  b
0  x  1
1  y  2
```

New behavior:

```
In [20]: df.groupby("a").apply(func)
x
y
Out[20]:
   a  b
0  x  1
1  y  2

[2 rows x 2 columns]
```

Concatenating sparse values

When passed DataFrames whose values are sparse, *concat()* will now return a *Series* or *DataFrame* with sparse values, rather than a SparseDataFrame (GH25702).

```
In [21]: df = pd.DataFrame({"A": pd.SparseArray([0, 1])})
```

Previous behavior:

```
In [2]: type(pd.concat([df, df]))
pandas.core.sparse.frame.SparseDataFrame
```

New behavior:

```
In [22]: type(pd.concat([df, df]))
Out[22]: pandas.core.frame.DataFrame
```

This now matches the existing behavior of *concat* on Series with sparse values. *concat()* will continue to return a SparseDataFrame when all the values are instances of SparseDataFrame.

This change also affects routines using *concat()* internally, like *get_dummies()*, which now returns a *DataFrame* in all cases (previously a SparseDataFrame was returned if all the columns were dummy encoded, and a *DataFrame* otherwise).

Providing any SparseSeries or SparseDataFrame to *concat()* will cause a SparseSeries or SparseDataFrame to be returned, as before.

The `.str`-accessor performs stricter type checks

Due to the lack of more fine-grained dtypes, *Series.str* so far only checked whether the data was of object dtype. *Series.str* will now infer the dtype data *within* the Series; in particular, 'bytes'-only data will raise an exception (except for *Series.str.decode()*, *Series.str.get()*, *Series.str.len()*, *Series.str.slice()*), see GH23163, GH23011, GH23551.

Previous behavior:

```
In [1]: s = pd.Series(np.array(['a', 'ba', 'cba'], 'S'), dtype=object)

In [2]: s
Out[2]:
0      b'a'
1     b'ba'
2    b'cba'
dtype: object

In [3]: s.str.startswith(b'a')
Out[3]:
0     True
1    False
2    False
dtype: bool
```

New behavior:

```
In [23]: s = pd.Series(np.array(['a', 'ba', 'cba'], 'S'), dtype=object)
```

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```
In [24]: s
Out[24]:
0      b'a'
1     b'ba'
2    b'cba'
Length: 3, dtype: object

In [25]: s.str.startswith(b'a')
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-25-ac784692b361> in <module>
----> 1 s.str.startswith(b'a')

/pandas/pandas/core/strings/accessor.py in wrapper(self, *args, **kwargs)
     98                     f"inferred dtype '{self._inferred_dtype}'."
     99                 )
--> 100                 raise TypeError(msg)
    101             return func(self, *args, **kwargs)
    102

TypeError: Cannot use .str.startswith with values of inferred dtype 'bytes'.
```

Categorical dtypes are preserved during GroupBy

Previously, columns that were categorical, but not the groupby key(s) would be converted to `object` dtype during groupby operations. pandas now will preserve these dtypes. (GH18502)

```
In [26]: cat = pd.Categorical(["foo", "bar", "bar", "qux"], ordered=True)

In [27]: df = pd.DataFrame({'payload': [-1, -2, -1, -2], 'col': cat})

In [28]: df
Out[28]:
   payload  col
0       -1  foo
1       -2  bar
2       -1  bar
3       -2  qux

[4 rows x 2 columns]

In [29]: df.dtypes
Out[29]:
payload       int64
col        category
Length: 2, dtype: object
```

Previous Behavior:

```
In [5]: df.groupby('payload').first().col.dtype
Out[5]: dtype('O')
```

New Behavior:

```
In [30]: df.groupby('payload').first().col.dtype
Out[30]: CategoricalDtype(categories=['bar', 'foo', 'qux'], ordered=True)
```

Incompatible Index type unions

When performing *Index.union()* operations between objects of incompatible dtypes, the result will be a base *Index* of dtype `object`. This behavior holds true for unions between *Index* objects that previously would have been prohibited. The dtype of empty *Index* objects will now be evaluated before performing union operations rather than simply returning the other *Index* object. *Index.union()* can now be considered commutative, such that `A.union(B) == B.union(A)` (GH23525).

Previous behavior:

```
In [1]: pd.period_range('19910905', periods=2).union(pd.Int64Index([1, 2, 3]))
...
ValueError: can only call with other PeriodIndex-ed objects

In [2]: pd.Index([], dtype=object).union(pd.Index([1, 2, 3]))
Out[2]: Int64Index([1, 2, 3], dtype='int64')
```

New behavior:

```
In [31]: pd.period_range('19910905', periods=2).union(pd.Int64Index([1, 2, 3]))
Out[31]: Index([1991-09-05, 1991-09-06, 1, 2, 3], dtype='object')

In [32]: pd.Index([], dtype=object).union(pd.Index([1, 2, 3]))
Out[32]: Index([1, 2, 3], dtype='object')
```

Note that integer- and floating-dtype indexes are considered "compatible". The integer values are coerced to floating point, which may result in loss of precision. See *Set operations on Index objects* for more.

`DataFrame` GroupBy ffill/bfill no longer return group labels

The methods `ffill`, `bfill`, `pad` and `backfill` of `DataFrameGroupBy` previously included the group labels in the return value, which was inconsistent with other groupby transforms. Now only the filled values are returned. (GH21521)

```
In [33]: df = pd.DataFrame({"a": ["x", "y"], "b": [1, 2]})

In [34]: df
Out[34]:
   a  b
0  x  1
1  y  2

[2 rows x 2 columns]
```

Previous behavior:

```
In [3]: df.groupby("a").ffill()
Out[3]:
   a  b
0  x  1
1  y  2
```

New behavior:

```
In [35]: df.groupby("a").ffill()
Out[35]:
   b
0  1
1  2

[2 rows x 1 columns]
```

`DataFrame` describe on an empty Categorical / object column will return top and freq

When calling *`DataFrame.describe()`* with an empty categorical / object column, the 'top' and 'freq' columns were previously omitted, which was inconsistent with the output for non-empty columns. Now the 'top' and 'freq' columns will always be included, with `numpy.nan` in the case of an empty *`DataFrame`* (GH26397)

```
In [36]: df = pd.DataFrame({"empty_col": pd.Categorical([])})

In [37]: df
Out[37]:
Empty DataFrame
Columns: [empty_col]
Index: []

[0 rows x 1 columns]
```

Previous behavior:

```
In [3]: df.describe()
Out[3]:
        empty_col
count           0
unique          0
```

New behavior:

```
In [38]: df.describe()
Out[38]:
       empty_col
count          0
unique         0
top          NaN
freq         NaN

[4 rows x 1 columns]
```

`__str__` methods now call `__repr__` rather than vice versa

pandas has until now mostly defined string representations in a pandas objects' `__str__`/`__unicode__`/`__bytes__` methods, and called `__str__` from the `__repr__` method, if a specific `__repr__` method is not found. This is not needed for Python3. In pandas 0.25, the string representations of pandas objects are now generally defined in `__repr__`, and calls to `__str__` in general now pass the call on to the `__repr__`, if a specific `__str__` method doesn't exist, as is standard for Python. This change is backward compatible for direct usage of pandas, but if you subclass pandas objects *and* give your subclasses specific `__str__`/`__repr__` methods, you may have to adjust your `__str__`/`__repr__` methods (GH26495).

Indexing an `IntervalIndex` with `Interval` objects

Indexing methods for *`IntervalIndex`* have been modified to require exact matches only for *`Interval`* queries. `IntervalIndex` methods previously matched on any overlapping `Interval`. Behavior with scalar points, e.g. querying with an integer, is unchanged (GH16316).

```
In [39]: ii = pd.IntervalIndex.from_tuples([(0, 4), (1, 5), (5, 8)])

In [40]: ii
Out[40]:
IntervalIndex([(0, 4], (1, 5], (5, 8]],
              closed='right',
              dtype='interval[int64]')
```

The `in` operator (`__contains__`) now only returns `True` for exact matches to `Intervals` in the `IntervalIndex`, whereas this would previously return `True` for any `Interval` overlapping an `Interval` in the `IntervalIndex`.

Previous behavior:

```
In [4]: pd.Interval(1, 2, closed='neither') in ii
Out[4]: True

In [5]: pd.Interval(-10, 10, closed='both') in ii
Out[5]: True
```

New behavior:

```
In [41]: pd.Interval(1, 2, closed='neither') in ii
Out[41]: False

In [42]: pd.Interval(-10, 10, closed='both') in ii
Out[42]: False
```

The *`get_loc()`* method now only returns locations for exact matches to `Interval` queries, as opposed to the previous behavior of returning locations for overlapping matches. A `KeyError` will be raised if an exact match is not found.

Previous behavior:

```
In [6]: ii.get_loc(pd.Interval(1, 5))
Out[6]: array([0, 1])

In [7]: ii.get_loc(pd.Interval(2, 6))
Out[7]: array([0, 1, 2])
```

New behavior:

```
In [6]: ii.get_loc(pd.Interval(1, 5))
Out[6]: 1

In [7]: ii.get_loc(pd.Interval(2, 6))
---------------------------------------------------------------------------
KeyError: Interval(2, 6, closed='right')
```

Likewise, *get_indexer()* and `get_indexer_non_unique()` will also only return locations for exact matches to `Interval` queries, with `-1` denoting that an exact match was not found.

These indexing changes extend to querying a *Series* or *DataFrame* with an `IntervalIndex` index.

```
In [43]: s = pd.Series(list('abc'), index=ii)

In [44]: s
Out[44]:
(0, 4]    a
(1, 5]    b
(5, 8]    c
Length: 3, dtype: object
```

Selecting from a `Series` or `DataFrame` using `[]` (`__getitem__`) or `loc` now only returns exact matches for `Interval` queries.

Previous behavior:

```
In [8]: s[pd.Interval(1, 5)]
Out[8]:
(0, 4]    a
(1, 5]    b
dtype: object

In [9]: s.loc[pd.Interval(1, 5)]
Out[9]:
(0, 4]    a
(1, 5]    b
dtype: object
```

New behavior:

```
In [45]: s[pd.Interval(1, 5)]
Out[45]: 'b'

In [46]: s.loc[pd.Interval(1, 5)]
Out[46]: 'b'
```

Similarly, a `KeyError` will be raised for non-exact matches instead of returning overlapping matches.

Previous behavior:

```
In [9]: s[pd.Interval(2, 3)]
Out[9]:
(0, 4]    a
(1, 5]    b
dtype: object

In [10]: s.loc[pd.Interval(2, 3)]
```

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```
Out[10]:
(0, 4]    a
(1, 5]    b
dtype: object
```

New behavior:

```
In [6]: s[pd.Interval(2, 3)]
---------------------------------------------------------------------------
KeyError: Interval(2, 3, closed='right')

In [7]: s.loc[pd.Interval(2, 3)]
---------------------------------------------------------------------------
KeyError: Interval(2, 3, closed='right')
```

The *overlaps()* method can be used to create a boolean indexer that replicates the previous behavior of returning overlapping matches.

New behavior:

```
In [47]: idxr = s.index.overlaps(pd.Interval(2, 3))

In [48]: idxr
Out[48]: array([ True,  True, False])

In [49]: s[idxr]
Out[49]:
(0, 4]    a
(1, 5]    b
Length: 2, dtype: object

In [50]: s.loc[idxr]
Out[50]:
(0, 4]    a
(1, 5]    b
Length: 2, dtype: object
```

Binary ufuncs on Series now align

Applying a binary ufunc like `numpy.power()` now aligns the inputs when both are *Series* (GH23293).

```
In [51]: s1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [52]: s2 = pd.Series([3, 4, 5], index=['d', 'c', 'b'])

In [53]: s1
Out[53]:
a    1
b    2
c    3
Length: 3, dtype: int64

In [54]: s2
Out[54]:
d    3
```

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```
c    4
b    5
Length: 3, dtype: int64
```

Previous behavior

```
In [5]: np.power(s1, s2)
Out[5]:
a      1
b     16
c    243
dtype: int64
```

New behavior

```
In [55]: np.power(s1, s2)
Out[55]:
a     1.0
b    32.0
c    81.0
d     NaN
Length: 4, dtype: float64
```

This matches the behavior of other binary operations in pandas, like *`Series.add()`*. To retain the previous behavior, convert the other `Series` to an array before applying the ufunc.

```
In [56]: np.power(s1, s2.array)
Out[56]:
a      1
b     16
c    243
Length: 3, dtype: int64
```

Categorical.argsort now places missing values at the end

`Categorical.argsort()` now places missing values at the end of the array, making it consistent with NumPy and the rest of pandas (GH21801).

```
In [57]: cat = pd.Categorical(['b', None, 'a'], categories=['a', 'b'], ordered=True)
```

Previous behavior

```
In [2]: cat = pd.Categorical(['b', None, 'a'], categories=['a', 'b'], ordered=True)

In [3]: cat.argsort()
Out[3]: array([1, 2, 0])

In [4]: cat[cat.argsort()]
Out[4]:
[NaN, a, b]
categories (2, object): [a < b]
```

New behavior

```
In [58]: cat.argsort()
Out[58]: array([2, 0, 1])

In [59]: cat[cat.argsort()]
Out[59]:
['a', 'b', NaN]
Categories (2, object): ['a' < 'b']
```

Column order is preserved when passing a list of dicts to DataFrame

Starting with Python 3.7 the key-order of `dict` is guaranteed. In practice, this has been true since Python 3.6. The *DataFrame* constructor now treats a list of dicts in the same way as it does a list of `OrderedDict`, i.e. preserving the order of the dicts. This change applies only when pandas is running on Python>=3.6 (GH27309).

```
In [60]: data = [
   ....:     {'name': 'Joe', 'state': 'NY', 'age': 18},
   ....:     {'name': 'Jane', 'state': 'KY', 'age': 19, 'hobby': 'Minecraft'},
   ....:     {'name': 'Jean', 'state': 'OK', 'age': 20, 'finances': 'good'}
   ....: ]
   ....:
```

Previous Behavior:

The columns were lexicographically sorted previously,

```
In [1]: pd.DataFrame(data)
Out[1]:
   age finances      hobby  name state
0   18      NaN        NaN   Joe    NY
1   19      NaN  Minecraft  Jane    KY
2   20     good        NaN  Jean    OK
```

New Behavior:

The column order now matches the insertion-order of the keys in the `dict`, considering all the records from top to bottom. As a consequence, the column order of the resulting DataFrame has changed compared to previous pandas versions.

```
In [61]: pd.DataFrame(data)
Out[61]:
   name state  age      hobby finances
0   Joe    NY   18        NaN      NaN
1  Jane    KY   19  Minecraft      NaN
2  Jean    OK   20        NaN     good

[3 rows x 5 columns]
```

Increased minimum versions for dependencies

Due to dropping support for Python 2.7, a number of optional dependencies have updated minimum versions (GH25725, GH24942, GH25752). Independently, some minimum supported versions of dependencies were updated (GH23519, GH25554). If installed, we now require:

Package	Minimum Version	Required
numpy	1.13.3	X
pytz	2015.4	X
python-dateutil	2.6.1	X
bottleneck	1.2.1	
numexpr	2.6.2	
pytest (dev)	4.0.2	

For optional libraries the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

Package	Minimum Version
beautifulsoup4	4.6.0
fastparquet	0.2.1
gcsfs	0.2.2
lxml	3.8.0
matplotlib	2.2.2
openpyxl	2.4.8
pyarrow	0.9.0
pymysql	0.7.1
pytables	3.4.2
scipy	0.19.0
sqlalchemy	1.1.4
xarray	0.8.2
xlrd	1.1.0
xlsxwriter	0.9.8
xlwt	1.2.0

See *Dependencies* and *Optional dependencies* for more.

Other API changes

- *DatetimeTZDtype* will now standardize pytz timezones to a common timezone instance (GH24713)
- *Timestamp* and *Timedelta* scalars now implement the `to_numpy()` method as aliases to *Timestamp.to_datetime64()* and *Timedelta.to_timedelta64()*, respectively. (GH24653)
- *Timestamp.strptime()* will now rise a `NotImplementedError` (GH25016)
- Comparing *Timestamp* with unsupported objects now returns `NotImplemented` instead of raising `TypeError`. This implies that unsupported rich comparisons are delegated to the other object, and are now consistent with Python 3 behavior for `datetime` objects (GH24011)
- Bug in *DatetimeIndex.snap()* which didn't preserving the `name` of the input *Index* (GH25575)
- The `arg` argument in `pandas.core.groupby.DataFrameGroupBy.agg()` has been renamed to `func` (GH26089)

- The `arg` argument in `pandas.core.window._Window.aggregate()` has been renamed to `func` (GH26372)
- Most pandas classes had a `__bytes__` method, which was used for getting a python2-style bytestring representation of the object. This method has been removed as a part of dropping Python2 (GH26447)
- The `.str`-accessor has been disabled for 1-level *MultiIndex*, use *MultiIndex.to_flat_index()* if necessary (GH23679)
- Removed support of gtk package for clipboards (GH26563)
- Using an unsupported version of Beautiful Soup 4 will now raise an `ImportError` instead of a `ValueError` (GH27063)
- *Series.to_excel()* and *DataFrame.to_excel()* will now raise a `ValueError` when saving timezone aware data. (GH27008, GH7056)
- `ExtensionArray.argsort()` places NA values at the end of the sorted array. (GH21801)
- *DataFrame.to_hdf()* and *Series.to_hdf()* will now raise a `NotImplementedError` when saving a *MultiIndex* with extension data types for a `fixed` format. (GH7775)
- Passing duplicate `names` in *read_csv()* will now raise a `ValueError` (GH17346)

Deprecations

Sparse subclasses

The `SparseSeries` and `SparseDataFrame` subclasses are deprecated. Their functionality is better-provided by a `Series` or `DataFrame` with sparse values.

Previous way

```
df = pd.SparseDataFrame({"A": [0, 0, 1, 2]})
df.dtypes
```

New way

```
In [62]: df = pd.DataFrame({"A": pd.SparseArray([0, 0, 1, 2])})

In [63]: df.dtypes
Out[63]:
A    Sparse[int64, 0]
Length: 1, dtype: object
```

The memory usage of the two approaches is identical. See *Migrating* for more (GH19239).

msgpack format

The msgpack format is deprecated as of 0.25 and will be removed in a future version. It is recommended to use pyarrow for on-the-wire transmission of pandas objects. (GH27084)

Other deprecations

- The deprecated `.ix[]` indexer now raises a more visible `FutureWarning` instead of `DeprecationWarning` (GH26438).
- Deprecated the `units=M` (months) and `units=Y` (year) parameters for `units` of *pandas.to_timedelta()*, *pandas.Timedelta()* and *pandas.TimedeltaIndex()* (GH16344)
- *pandas.concat()* has deprecated the `join_axes`-keyword. Instead, use *DataFrame.reindex()* or *DataFrame.reindex_like()* on the result or on the inputs (GH21951)
- The `SparseArray.values` attribute is deprecated. You can use `np.asarray(...)` or the `SparseArray.to_dense()` method instead (GH26421).
- The functions *pandas.to_datetime()* and *pandas.to_timedelta()* have deprecated the `box` keyword. Instead, use `to_numpy()` or *Timestamp.to_datetime64()* or *Timedelta.to_timedelta64()*. (GH24416)
- The `DataFrame.compound()` and `Series.compound()` methods are deprecated and will be removed in a future version (GH26405).
- The internal attributes `_start`, `_stop` and `_step` attributes of *RangeIndex* have been deprecated. Use the public attributes *start*, *stop* and *step* instead (GH26581).
- The `Series.ftype()`, `Series.ftypes()` and `DataFrame.ftypes()` methods are deprecated and will be removed in a future version. Instead, use *Series.dtype()* and *DataFrame.dtypes()* (GH26705).
- The `Series.get_values()`, `DataFrame.get_values()`, `Index.get_values()`, `SparseArray.get_values()` and `Categorical.get_values()` methods are deprecated. One of `np.asarray(..)` or *to_numpy()* can be used instead (GH19617).
- The 'outer' method on NumPy ufuncs, e.g. `np.subtract.outer` has been deprecated on *Series* objects. Convert the input to an array with *Series.array* first (GH27186)
- *Timedelta.resolution()* is deprecated and replaced with *Timedelta.resolution_string()*. In a future version, *Timedelta.resolution()* will be changed to behave like the standard library `datetime.timedelta.resolution` (GH21344)
- *read_table()* has been undeprecated. (GH25220)
- `Index.dtype_str` is deprecated. (GH18262)
- `Series.imag` and `Series.real` are deprecated. (GH18262)
- `Series.put()` is deprecated. (GH18262)
- *Index.item()* and *Series.item()* is deprecated. (GH18262)
- The default value `ordered=None` in `CategoricalDtype` has been deprecated in favor of `ordered=False`. When converting between categorical types `ordered=True` must be explicitly passed in order to be preserved. (GH26336)
- `Index.contains()` is deprecated. Use `key in index` (`__contains__`) instead (GH17753).
- `DataFrame.get_dtype_counts()` is deprecated. (GH18262)
- `Categorical.ravel()` will return a *Categorical* instead of a `np.ndarray` (GH27199)

Removal of prior version deprecations/changes

- Removed `Panel` (GH25047, GH25191, GH25231)
- Removed the previously deprecated `sheetname` keyword in *`read_excel()`* (GH16442, GH20938)
- Removed the previously deprecated `TimeGrouper` (GH16942)
- Removed the previously deprecated `parse_cols` keyword in *`read_excel()`* (GH16488)
- Removed the previously deprecated `pd.options.html.border` (GH16970)
- Removed the previously deprecated `convert_objects` (GH11221)
- Removed the previously deprecated `select` method of `DataFrame` and `Series` (GH17633)
- Removed the previously deprecated behavior of *`Series`* treated as list-like in *`rename_categories()`* (GH17982)
- Removed the previously deprecated `DataFrame.reindex_axis` and `Series.reindex_axis` (GH17842)
- Removed the previously deprecated behavior of altering column or index labels with *`Series.rename_axis()`* or *`DataFrame.rename_axis()`* (GH17842)
- Removed the previously deprecated `tupleize_cols` keyword argument in *`read_html()`*, *`read_csv()`*, and *`DataFrame.to_csv()`* (GH17877, GH17820)
- Removed the previously deprecated `DataFrame.from.csv` and `Series.from_csv` (GH17812)
- Removed the previously deprecated `raise_on_error` keyword argument in *`DataFrame.where()`* and *`DataFrame.mask()`* (GH17744)
- Removed the previously deprecated `ordered` and `categories` keyword arguments in `astype` (GH17742)
- Removed the previously deprecated `cdate_range` (GH17691)
- Removed the previously deprecated `True` option for the `dropna` keyword argument in `SeriesGroupBy.nth()` (GH17493)
- Removed the previously deprecated `convert` keyword argument in *`Series.take()`* and *`DataFrame.take()`* (GH17352)
- Removed the previously deprecated behavior of arithmetic operations with `datetime.date` objects (GH21152)

Performance improvements

- Significant speedup in `SparseArray` initialization that benefits most operations, fixing performance regression introduced in v0.20.0 (GH24985)
- *`DataFrame.to_stata()`* is now faster when outputting data with any string or non-native endian columns (GH25045)
- Improved performance of *`Series.searchsorted()`*. The speedup is especially large when the dtype is int8/int16/int32 and the searched key is within the integer bounds for the dtype (GH22034)
- Improved performance of `pandas.core.groupby.GroupBy.quantile()` (GH20405)
- Improved performance of slicing and other selected operation on a *`RangeIndex`* (GH26565, GH26617, GH26722)
- *`RangeIndex`* now performs standard lookup without instantiating an actual hashtable, hence saving memory (GH16685)

- Improved performance of *read_csv()* by faster tokenizing and faster parsing of small float numbers (GH25784)
- Improved performance of *read_csv()* by faster parsing of N/A and boolean values (GH25804)
- Improved performance of `IntervalIndex.is_monotonic`, `IntervalIndex.is_monotonic_increasing` and `IntervalIndex.is_monotonic_decreasing` by removing conversion to *MultiIndex* (GH24813)
- Improved performance of *DataFrame.to_csv()* when writing datetime dtypes (GH25708)
- Improved performance of *read_csv()* by much faster parsing of `MM/YYYY` and `DD/MM/YYYY` datetime formats (GH25922)
- Improved performance of nanops for dtypes that cannot store NaNs. Speedup is particularly prominent for *Series.all()* and *Series.any()* (GH25070)
- Improved performance of *Series.map()* for dictionary mappers on categorical series by mapping the categories instead of mapping all values (GH23785)
- Improved performance of `IntervalIndex.intersection()` (GH24813)
- Improved performance of *read_csv()* by faster concatenating date columns without extra conversion to string for integer/float zero and float `NaN`; by faster checking the string for the possibility of being a date (GH25754)
- Improved performance of `IntervalIndex.is_unique` by removing conversion to `MultiIndex` (GH24813)
- Restored performance of `DatetimeIndex.__iter__()` by re-enabling specialized code path (GH26702)
- Improved performance when building *MultiIndex* with at least one *CategoricalIndex* level (GH22044)
- Improved performance by removing the need for a garbage collect when checking for `SettingWithCopyWarning` (GH27031)
- For *to_datetime()* changed default value of cache parameter to `True` (GH26043)
- Improved performance of *DatetimeIndex* and *PeriodIndex* slicing given non-unique, monotonic data (GH27136).
- Improved performance of `pd.read_json()` for index-oriented data. (GH26773)
- Improved performance of `MultiIndex.shape()` (GH27384).

Bug fixes

Categorical

- Bug in *DataFrame.at()* and *Series.at()* that would raise exception if the index was a *CategoricalIndex* (GH20629)
- Fixed bug in comparison of ordered *Categorical* that contained missing values with a scalar which sometimes incorrectly resulted in `True` (GH26504)
- Bug in *DataFrame.dropna()* when the *DataFrame* has a *CategoricalIndex* containing *Interval* objects incorrectly raised a `TypeError` (GH25087)

Datetimelike

- Bug in *to_datetime()* which would raise an (incorrect) ValueError when called with a date far into the future and the format argument specified instead of raising OutOfBoundsDatetime (GH23830)
- Bug in *to_datetime()* which would raise InvalidIndexError: Reindexing only valid with uniquely valued Index objects when called with cache=True, with arg including at least two different elements from the set {None, numpy.nan, pandas.NaT} (GH22305)
- Bug in *DataFrame* and *Series* where timezone aware data with dtype='datetime64[ns] was not cast to naive (GH25843)
- Improved *Timestamp* type checking in various datetime functions to prevent exceptions when using a subclassed datetime (GH25851)
- Bug in *Series* and *DataFrame* repr where np.datetime64('NaT') and np.timedelta64('NaT') with dtype=object would be represented as NaN (GH25445)
- Bug in *to_datetime()* which does not replace the invalid argument with NaT when error is set to coerce (GH26122)
- Bug in adding DateOffset with nonzero month to *DatetimeIndex* would raise ValueError (GH26258)
- Bug in *to_datetime()* which raises unhandled OverflowError when called with mix of invalid dates and NaN values with format='%Y%m%d' and error='coerce' (GH25512)
- Bug in isin() for datetimelike indexes; *DatetimeIndex*, *TimedeltaIndex* and *PeriodIndex* where the levels parameter was ignored. (GH26675)
- Bug in *to_datetime()* which raises TypeError for format='%Y%m%d' when called for invalid integer dates with length >= 6 digits with errors='ignore'
- Bug when comparing a *PeriodIndex* against a zero-dimensional numpy array (GH26689)
- Bug in constructing a Series or DataFrame from a numpy datetime64 array with a non-ns unit and out-of-bound timestamps generating rubbish data, which will now correctly raise an OutOfBoundsDatetime error (GH26206).
- Bug in *date_range()* with unnecessary OverflowError being raised for very large or very small dates (GH26651)
- Bug where adding *Timestamp* to a np.timedelta64 object would raise instead of returning a *Timestamp* (GH24775)
- Bug where comparing a zero-dimensional numpy array containing a np.datetime64 object to a *Timestamp* would incorrect raise TypeError (GH26916)
- Bug in *to_datetime()* which would raise ValueError: Tz-aware datetime.datetime cannot be converted to datetime64 unless utc=True when called with cache=True, with arg including datetime strings with different offset (GH26097)
-

Timedelta

- Bug in `TimedeltaIndex.intersection()` where for non-monotonic indices in some cases an empty `Index` was returned when in fact an intersection existed (GH25913)
- Bug with comparisons between *`Timedelta`* and `NaT` raising `TypeError` (GH26039)
- Bug when adding or subtracting a `BusinessHour` to a *`Timestamp`* with the resulting time landing in a following or prior day respectively (GH26381)
- Bug when comparing a *`TimedeltaIndex`* against a zero-dimensional numpy array (GH26689)

Timezones

- Bug in *`DatetimeIndex.to_frame()`* where timezone aware data would be converted to timezone naive data (GH25809)
- Bug in *`to_datetime()`* with `utc=True` and datetime strings that would apply previously parsed UTC offsets to subsequent arguments (GH24992)
- Bug in *`Timestamp.tz_localize()`* and *`Timestamp.tz_convert()`* does not propagate `freq` (GH25241)
- Bug in *`Series.at()`* where setting *`Timestamp`* with timezone raises `TypeError` (GH25506)
- Bug in *`DataFrame.update()`* when updating with timezone aware data would return timezone naive data (GH25807)
- Bug in *`to_datetime()`* where an uninformative `RuntimeError` was raised when passing a naive *`Timestamp`* with datetime strings with mixed UTC offsets (GH25978)
- Bug in *`to_datetime()`* with `unit='ns'` would drop timezone information from the parsed argument (GH26168)
- Bug in *`DataFrame.join()`* where joining a timezone aware index with a timezone aware column would result in a column of `NaN` (GH26335)
- Bug in *`date_range()`* where ambiguous or nonexistent start or end times were not handled by the `ambiguous` or `nonexistent` keywords respectively (GH27088)
- Bug in `DatetimeIndex.union()` when combining a timezone aware and timezone unaware *`DatetimeIndex`* (GH21671)
- Bug when applying a numpy reduction function (e.g. `numpy.minimum()`) to a timezone aware *`Series`* (GH15552)

Numeric

- Bug in *`to_numeric()`* in which large negative numbers were being improperly handled (GH24910)
- Bug in *`to_numeric()`* in which numbers were being coerced to float, even though `errors` was not `coerce` (GH24910)
- Bug in *`to_numeric()`* in which invalid values for `errors` were being allowed (GH26466)
- Bug in `format` in which floating point complex numbers were not being formatted to proper display precision and trimming (GH25514)
- Bug in error messages in *`DataFrame.corr()`* and *`Series.corr()`*. Added the possibility of using a callable. (GH25729)

- Bug in *Series.divmod()* and *Series.rdivmod()* which would raise an (incorrect) ValueError rather than return a pair of *Series* objects as result (GH25557)
- Raises a helpful exception when a non-numeric index is sent to interpolate() with methods which require numeric index. (GH21662)
- Bug in *eval()* when comparing floats with scalar operators, for example: x < -0.1 (GH25928)
- Fixed bug where casting all-boolean array to integer extension array failed (GH25211)
- Bug in divmod with a *Series* object containing zeros incorrectly raising AttributeError (GH26987)
- Inconsistency in *Series* floor-division (//) and divmod filling positive//zero with NaN instead of Inf (GH27321)
-

Conversion

- Bug in *DataFrame.astype()* when passing a dict of columns and types the errors parameter was ignored. (GH25905)
-

Strings

- Bug in the __name__ attribute of several methods of *Series.str*, which were set incorrectly (GH23551)
- Improved error message when passing *Series* of wrong dtype to *Series.str.cat()* (GH22722)
-

Interval

- Construction of *Interval* is restricted to numeric, *Timestamp* and *Timedelta* endpoints (GH23013)
- Fixed bug in *Series*/*DataFrame* not displaying NaN in *IntervalIndex* with missing values (GH25984)
- Bug in *IntervalIndex.get_loc()* where a KeyError would be incorrectly raised for a decreasing *IntervalIndex* (GH25860)
- Bug in *Index* constructor where passing mixed closed *Interval* objects would result in a ValueError instead of an object dtype Index (GH27172)

Indexing

- Improved exception message when calling *DataFrame.iloc()* with a list of non-numeric objects (GH25753).
- Improved exception message when calling .iloc or .loc with a boolean indexer with different length (GH26658).
- Bug in KeyError exception message when indexing a *MultiIndex* with a non-existent key not displaying the original key (GH27250).
- Bug in .iloc and .loc with a boolean indexer not raising an IndexError when too few items are passed (GH26658).

- Bug in *DataFrame.loc()* and *Series.loc()* where KeyError was not raised for a MultiIndex when the key was less than or equal to the number of levels in the *MultiIndex* (GH14885).
- Bug in which *DataFrame.append()* produced an erroneous warning indicating that a KeyError will be thrown in the future when the data to be appended contains new columns (GH22252).
- Bug in which *DataFrame.to_csv()* caused a segfault for a reindexed data frame, when the indices were single-level *MultiIndex* (GH26303).
- Fixed bug where assigning a *arrays.PandasArray* to a pandas.core.frame.DataFrame would raise error (GH26390)
- Allow keyword arguments for callable local reference used in the *DataFrame.query()* string (GH26426)
- Fixed a KeyError when indexing a MultiIndex` level with a list containing exactly one label, which is missing (GH27148)
- Bug which produced AttributeError on partial matching *Timestamp* in a *MultiIndex* (GH26944)
- Bug in *Categorical* and *CategoricalIndex* with *Interval* values when using the in operator (__contains) with objects that are not comparable to the values in the Interval (GH23705)
- Bug in *DataFrame.loc()* and *DataFrame.iloc()* on a *DataFrame* with a single timezone-aware datetime64[ns] column incorrectly returning a scalar instead of a *Series* (GH27110)
- Bug in *CategoricalIndex* and *Categorical* incorrectly raising ValueError instead of TypeError when a list is passed using the in operator (__contains__) (GH21729)
- Bug in setting a new value in a *Series* with a *Timedelta* object incorrectly casting the value to an integer (GH22717)
- Bug in *Series* setting a new key (__setitem__) with a timezone-aware datetime incorrectly raising ValueError (GH12862)
- Bug in *DataFrame.iloc()* when indexing with a read-only indexer (GH17192)
- Bug in *Series* setting an existing tuple key (__setitem__) with timezone-aware datetime values incorrectly raising TypeError (GH20441)

Missing

- Fixed misleading exception message in *Series.interpolate()* if argument order is required, but omitted (GH10633, GH24014).
- Fixed class type displayed in exception message in *DataFrame.dropna()* if invalid axis parameter passed (GH25555)
- A ValueError will now be thrown by *DataFrame.fillna()* when limit is not a positive integer (GH27042)
-

MultiIndex

- Bug in which incorrect exception raised by *Timedelta* when testing the membership of *MultiIndex* (GH24570)
-

IO

- Bug in *DataFrame.to_html()* where values were truncated using display options instead of outputting the full content (GH17004)
- Fixed bug in missing text when using `to_clipboard()` if copying utf-16 characters in Python 3 on Windows (GH25040)
- Bug in *read_json()* for `orient='table'` when it tries to infer dtypes by default, which is not applicable as dtypes are already defined in the JSON schema (GH21345)
- Bug in *read_json()* for `orient='table'` and float index, as it infers index dtype by default, which is not applicable because index dtype is already defined in the JSON schema (GH25433)
- Bug in *read_json()* for `orient='table'` and string of float column names, as it makes a column name type conversion to *Timestamp*, which is not applicable because column names are already defined in the JSON schema (GH25435)
- Bug in *json_normalize()* for `errors='ignore'` where missing values in the input data, were filled in resulting `DataFrame` with the string `"nan"` instead of `numpy.nan` (GH25468)
- *DataFrame.to_html()* now raises `TypeError` when using an invalid type for the `classes` parameter instead of `AssertionError` (GH25608)
- Bug in *DataFrame.to_string()* and *DataFrame.to_latex()* that would lead to incorrect output when the `header` keyword is used (GH16718)
- Bug in *read_csv()* not properly interpreting the UTF8 encoded filenames on Windows on Python 3.6+ (GH15086)
- Improved performance in *pandas.read_stata()* and `pandas.io.stata.StataReader` when converting columns that have missing values (GH25772)
- Bug in *DataFrame.to_html()* where header numbers would ignore display options when rounding (GH17280)
- Bug in *read_hdf()* where reading a table from an HDF5 file written directly with PyTables fails with a `ValueError` when using a sub-selection via the `start` or `stop` arguments (GH11188)
- Bug in *read_hdf()* not properly closing store after a `KeyError` is raised (GH25766)
- Improved the explanation for the failure when value labels are repeated in Stata dta files and suggested workarounds (GH25772)
- Improved *pandas.read_stata()* and `pandas.io.stata.StataReader` to read incorrectly formatted 118 format files saved by Stata (GH25960)
- Improved the `col_space` parameter in *DataFrame.to_html()* to accept a string so CSS length values can be set correctly (GH25941)
- Fixed bug in loading objects from S3 that contain `#` characters in the URL (GH25945)
- Adds `use_bqstorage_api` parameter to *read_gbq()* to speed up downloads of large data frames. This feature requires version 0.10.0 of the `pandas-gbq` library as well as the `google-cloud-bigquery-storage` and `fastavro` libraries. (GH26104)

- Fixed memory leak in *DataFrame.to_json()* when dealing with numeric data (GH24889)
- Bug in *read_json()* where date strings with `Z` were not converted to a UTC timezone (GH26168)
- Added `cache_dates=True` parameter to *read_csv()*, which allows to cache unique dates when they are parsed (GH25990)
- *DataFrame.to_excel()* now raises a `ValueError` when the caller's dimensions exceed the limitations of Excel (GH26051)
- Fixed bug in *pandas.read_csv()* where a BOM would result in incorrect parsing using engine='python' (GH26545)
- *read_excel()* now raises a `ValueError` when input is of type `pandas.io.excel.ExcelFile` and `engine` param is passed since `pandas.io.excel.ExcelFile` has an engine defined (GH26566)
- Bug while selecting from `HDFStore` with `where=''` specified (GH26610).
- Fixed bug in *DataFrame.to_excel()* where custom objects (i.e. `PeriodIndex`) inside merged cells were not being converted into types safe for the Excel writer (GH27006)
- Bug in *read_hdf()* where reading a timezone aware *DatetimeIndex* would raise a `TypeError` (GH11926)
- Bug in `to_msgpack()` and `read_msgpack()` which would raise a `ValueError` rather than a `FileNotFoundError` for an invalid path (GH27160)
- Fixed bug in *DataFrame.to_parquet()* which would raise a `ValueError` when the dataframe had no columns (GH27339)
- Allow parsing of *PeriodDtype* columns when using *read_csv()* (GH26934)

Plotting

- Fixed bug where *api.extensions.ExtensionArray* could not be used in matplotlib plotting (GH25587)
- Bug in an error message in *DataFrame.plot()*. Improved the error message if non-numerics are passed to *DataFrame.plot()* (GH25481)
- Bug in incorrect ticklabel positions when plotting an index that are non-numeric / non-datetime (GH7612, GH15912, GH22334)
- Fixed bug causing plots of *PeriodIndex* timeseries to fail if the frequency is a multiple of the frequency rule code (GH14763)
- Fixed bug when plotting a *DatetimeIndex* with `datetime.timezone.utc` timezone (GH17173)
-

GroupBy/resample/rolling

- Bug in `pandas.core.resample.Resampler.agg()` with a timezone aware index where `OverflowError` would raise when passing a list of functions (GH22660)
- Bug in *pandas.core.groupby.DataFrameGroupBy.nunique()* in which the names of column levels were lost (GH23222)
- Bug in *pandas.core.groupby.GroupBy.agg()* when applying an aggregation function to timezone aware data (GH23683)

- Bug in *pandas.core.groupby.GroupBy.first()* and *pandas.core.groupby.GroupBy.last()* where timezone information would be dropped (GH21603)
- Bug in *pandas.core.groupby.GroupBy.size()* when grouping only NA values (GH23050)
- Bug in *Series.groupby()* where `observed` kwarg was previously ignored (GH24880)
- Bug in *Series.groupby()* where using `groupby` with a *MultiIndex* Series with a list of labels equal to the length of the series caused incorrect grouping (GH25704)
- Ensured that ordering of outputs in `groupby` aggregation functions is consistent across all versions of Python (GH25692)
- Ensured that result group order is correct when grouping on an ordered `Categorical` and specifying `observed=True` (GH25871, GH25167)
- Bug in `pandas.core.window.Rolling.min()` and `pandas.core.window.Rolling.max()` that caused a memory leak (GH25893)
- Bug in `pandas.core.window.Rolling.count()` and `pandas.core.window.Expanding.count` was previously ignoring the `axis` keyword (GH13503)
- Bug in `pandas.core.groupby.GroupBy.idxmax()` and `pandas.core.groupby.GroupBy.idxmin()` with datetime column would return incorrect dtype (GH25444, GH15306)
- Bug in *pandas.core.groupby.GroupBy.cumsum()*, *pandas.core.groupby.GroupBy.cumprod()*, *pandas.core.groupby.GroupBy.cummin()* and *pandas.core.groupby.GroupBy.cummax()* with categorical column having absent categories, would return incorrect result or segfault (GH16771)
- Bug in *pandas.core.groupby.GroupBy.nth()* where NA values in the grouping would return incorrect results (GH26011)
- Bug in *pandas.core.groupby.SeriesGroupBy.transform()* where transforming an empty group would raise a `ValueError` (GH26208)
- Bug in `pandas.core.frame.DataFrame.groupby()` where passing a `pandas.core.groupby.grouper.Grouper` would return incorrect groups when using the `.groups` accessor (GH26326)
- Bug in *pandas.core.groupby.GroupBy.agg()* where incorrect results are returned for uint64 columns. (GH26310)
- Bug in `pandas.core.window.Rolling.median()` and `pandas.core.window.Rolling.quantile()` where MemoryError is raised with empty window (GH26005)
- Bug in `pandas.core.window.Rolling.median()` and `pandas.core.window.Rolling.quantile()` where incorrect results are returned with `closed='left'` and `closed='neither'` (GH26005)
- Improved `pandas.core.window.Rolling`, `pandas.core.window.Window` and `pandas.core.window.ExponentialMovingWindow` functions to exclude nuisance columns from results instead of raising errors and raise a `DataError` only if all columns are nuisance (GH12537)
- Bug in `pandas.core.window.Rolling.max()` and `pandas.core.window.Rolling.min()` where incorrect results are returned with an empty variable window (GH26005)
- Raise a helpful exception when an unsupported weighted window function is used as an argument of `pandas.core.window.Window.aggregate()` (GH26597)

Reshaping

- Bug in *pandas.merge()* adds a string of None, if None is assigned in suffixes instead of remain the column name as-is (GH24782).
- Bug in *merge()* when merging by index name would sometimes result in an incorrectly numbered index (missing index values are now assigned NA) (GH24212, GH25009)
- to_records() now accepts dtypes to its column_dtypes parameter (GH24895)
- Bug in *concat()* where order of OrderedDict (and dict in Python 3.6+) is not respected, when passed in as objs argument (GH21510)
- Bug in *pivot_table()* where columns with NaN values are dropped even if dropna argument is False, when the aggfunc argument contains a list (GH22159)
- Bug in *concat()* where the resulting freq of two *DatetimeIndex* with the same freq would be dropped (GH3232).
- Bug in *merge()* where merging with equivalent Categorical dtypes was raising an error (GH22501)
- bug in *DataFrame* instantiating with a dict of iterators or generators (e.g. pd.DataFrame({'A': reversed(range(3))})) raised an error (GH26349).
- Bug in *DataFrame* instantiating with a range (e.g. pd.DataFrame(range(3))) raised an error (GH26342).
- Bug in *DataFrame* constructor when passing non-empty tuples would cause a segmentation fault (GH25691)
- Bug in *Series.apply()* failed when the series is a timezone aware *DatetimeIndex* (GH25959)
- Bug in *pandas.cut()* where large bins could incorrectly raise an error due to an integer overflow (GH26045)
- Bug in *DataFrame.sort_index()* where an error is thrown when a multi-indexed DataFrame is sorted on all levels with the initial level sorted last (GH26053)
- Bug in *Series.nlargest()* treats True as smaller than False (GH26154)
- Bug in *DataFrame.pivot_table()* with a *IntervalIndex* as pivot index would raise TypeError (GH25814)
- Bug in which *DataFrame.from_dict()* ignored order of OrderedDict when orient='index' (GH8425).
- Bug in *DataFrame.transpose()* where transposing a DataFrame with a timezone-aware datetime column would incorrectly raise ValueError (GH26825)
- Bug in *pivot_table()* when pivoting a timezone aware column as the values would remove timezone information (GH14948)
- Bug in *merge_asof()* when specifying multiple by columns where one is datetime64[ns, tz] dtype (GH26649)

Sparse

- Significant speedup in `SparseArray` initialization that benefits most operations, fixing performance regression introduced in v0.20.0 (GH24985)
- Bug in `SparseFrame` constructor where passing `None` as the data would cause `default_fill_value` to be ignored (GH16807)
- Bug in `SparseDataFrame` when adding a column in which the length of values does not match length of index, `AssertionError` is raised instead of raising `ValueError` (GH25484)
- Introduce a better error message in *`Series.sparse.from_coo()`* so it returns a `TypeError` for inputs that are not coo matrices (GH26554)
- Bug in `numpy.modf()` on a `SparseArray`. Now a tuple of `SparseArray` is returned (GH26946).

Build changes

- Fix install error with PyPy on macOS (GH26536)

ExtensionArray

- Bug in *`factorize()`* when passing an `ExtensionArray` with a custom `na_sentinel` (GH25696).
- *`Series.count()`* miscounts NA values in ExtensionArrays (GH26835)
- Added `Series.__array_ufunc__` to better handle NumPy ufuncs applied to Series backed by extension arrays (GH23293).
- Keyword argument `deep` has been removed from `ExtensionArray.copy()` (GH27083)

Other

- Removed unused C functions from vendored UltraJSON implementation (GH26198)
- Allow *`Index`* and *`RangeIndex`* to be passed to numpy `min` and `max` functions (GH26125)
- Use actual class name in repr of empty objects of a `Series` subclass (GH27001).
- Bug in *`DataFrame`* where passing an object array of timezone-aware `datetime` objects would incorrectly raise `ValueError` (GH13287)

Contributors

A total of 231 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.5 Version 0.24

5.5.1 What's new in 0.24.2 (March 12, 2019)

Warning: The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See Dropping Python 2.7 for more.

These are the changes in pandas 0.24.2. See *Release notes* for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in *DataFrame.all()* and *DataFrame.any()* where `bool_only=True` was ignored (GH25101)
- Fixed issue in `DataFrame` construction with passing a mixed list of mixed types could segfault. (GH25075)
- Fixed regression in *DataFrame.apply()* causing `RecursionError` when `dict`-like classes were passed as argument. (GH25196)
- Fixed regression in *DataFrame.replace()* where `regex=True` was only replacing patterns matching the start of the string (GH25259)
- Fixed regression in *DataFrame.duplicated()*, where empty dataframe was not returning a boolean dtyped Series. (GH25184)
- Fixed regression in *Series.min()* and *Series.max()* where `numeric_only=True` was ignored when the `Series` contained `Categorical` data (GH25299)
- Fixed regression in subtraction between *Series* objects with `datetime64[ns]` dtype incorrectly raising `OverflowError` when the `Series` on the right contains null values (GH25317)
- Fixed regression in *TimedeltaIndex* where `np.sum(index)` incorrectly returned a zero-dimensional object instead of a scalar (GH25282)
- Fixed regression in `IntervalDtype` construction where passing an incorrect string with 'Interval' as a prefix could result in a `RecursionError`. (GH25338)
- Fixed regression in creating a period-dtype array from a read-only NumPy array of period objects. (GH25403)

- Fixed regression in *Categorical*, where constructing it from a categorical Series and an explicit categories= that differed from that in the Series created an invalid object which could trigger segfaults. (GH25318)
- Fixed regression in *to_timedelta()* losing precision when converting floating data to Timedelta data (GH25077).
- Fixed pip installing from source into an environment without NumPy (GH25193)
- Fixed regression in *DataFrame.replace()* where large strings of numbers would be coerced into int64, causing an OverflowError (GH25616)
- Fixed regression in *factorize()* when passing a custom na_sentinel value with sort=True (GH25409).
- Fixed regression in *DataFrame.to_csv()* writing duplicate line endings with gzip compress (GH25311)

Bug fixes

I/O

- Better handling of terminal printing when the terminal dimensions are not known (GH25080)
- Bug in reading a HDF5 table-format DataFrame created in Python 2, in Python 3 (GH24925)
- Bug in reading a JSON with orient='table' generated by *DataFrame.to_json()* with index=False (GH25170)
- Bug where float indexes could have misaligned values when printing (GH25061)

Categorical

- Bug where calling *Series.replace()* on categorical data could return a Series with incorrect dimensions (GH24971)
-

Reshaping

- Bug in transform() where applying a function to a timezone aware column would return a timezone naive result (GH24198)
- Bug in *DataFrame.join()* when joining on a timezone aware *DatetimeIndex* (GH23931)

Visualization

- Bug in *Series.plot()* where a secondary y axis could not be set to log scale (GH25545)

Other

- Bug in *Series.is_unique()* where single occurrences of NaN were not considered unique (GH25180)
- Bug in *merge()* when merging an empty DataFrame with an Int64 column or a non-empty DataFrame with an Int64 column that is all NaN (GH25183)
- Bug in IntervalTree where a RecursionError occurs upon construction due to an overflow when adding endpoints, which also causes *IntervalIndex* to crash during indexing operations (GH25485)
- Bug in *Series.size* raising for some extension-array-backed Series, rather than returning the size (GH25580)
- Bug in resampling raising for nullable integer-dtype columns (GH25580)

Contributors

A total of 25 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.5.2 What's new in 0.24.1 (February 3, 2019)

Warning: The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See Dropping Python 2.7 for more.

These are the changes in pandas 0.24.1. See *Release notes* for a full changelog including other versions of pandas. See *What's new in 0.24.0 (January 25, 2019)* for the 0.24.0 changelog.

API changes

Changing the `sort` parameter for `Index` set operations

The default `sort` value for *`Index.union()`* has changed from `True` to `None` (GH24959). The default *behavior*, however, remains the same: the result is sorted, unless

1. `self` and `other` are identical
2. `self` or `other` is empty
3. `self` or `other` contain values that can not be compared (a `RuntimeWarning` is raised).

This change will allow `sort=True` to mean "always sort" in a future release.

The same change applies to *`Index.difference()`* and *`Index.symmetric_difference()`*, which would not sort the result when the values could not be compared.

The `sort` option for *`Index.intersection()`* has changed in three ways.

1. The default has changed from `True` to `False`, to restore the pandas 0.23.4 and earlier behavior of not sorting by default.
2. The behavior of `sort=True` can now be obtained with `sort=None`. This will sort the result only if the values in `self` and `other` are not identical.
3. The value `sort=True` is no longer allowed. A future version of pandas will properly support `sort=True` meaning "always sort".

Fixed regressions

- Fixed regression in *`DataFrame.to_dict()`* with `records` orient raising an `AttributeError` when the `DataFrame` contained more than 255 columns, or wrongly converting column names that were not valid python identifiers (GH24939, GH24940).
- Fixed regression in *`read_sql()`* when passing certain queries with MySQL/pymysql (GH24988).
- Fixed regression in *`Index.intersection`* incorrectly sorting the values by default (GH24959).
- Fixed regression in *`merge()`* when merging an empty `DataFrame` with multiple timezone-aware columns on one of the timezone-aware columns (GH25014).
- Fixed regression in *`Series.rename_axis()`* and *`DataFrame.rename_axis()`* where passing `None` failed to remove the axis name (GH25034)
- Fixed regression in *`to_timedelta()`* with `box=False` incorrectly returning a `datetime64` object instead of a `timedelta64` object (GH24961)
- Fixed regression where custom hashable types could not be used as column keys in *`DataFrame.set_index()`* (GH24969)

Bug fixes

Reshaping

- Bug in `DataFrame.groupby()` with `Grouper` when there is a time change (DST) and grouping frequency is `'1d'` (GH24972)

Visualization

- Fixed the warning for implicitly registered matplotlib converters not showing. See *Restore Matplotlib datetime converter registration* for more (GH24963).

Other

- Fixed AttributeError when printing a DataFrame's HTML repr after accessing the IPython config object (GH25036)

Contributors

A total of 7 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.5.3 What's new in 0.24.0 (January 25, 2019)

Warning: The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See Dropping Python 2.7 for more details.

This is a major release from 0.23.4 and includes a number of API changes, new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- *Optional Integer NA Support*
- *New APIs for accessing the array backing a Series or Index*
- *A new top-level method for creating arrays*
- *Store Interval and Period data in a Series or DataFrame*
- *Support for joining on two MultiIndexes*

Check the *API Changes* and *deprecations* before updating.

These are the changes in pandas 0.24.0. See *Release notes* for a full changelog including other versions of pandas.

Enhancements

Optional integer NA support

pandas has gained the ability to hold integer dtypes with missing values. This long requested feature is enabled through the use of *extension types*.

Note: IntegerArray is currently experimental. Its API or implementation may change without warning.

We can construct a `Series` with the specified dtype. The dtype string `Int64` is a pandas `ExtensionDtype`. Specifying a list or array using the traditional missing value marker of `np.nan` will infer to integer dtype. The display of the `Series` will also use the `NaN` to indicate missing values in string outputs. (GH20700, GH20747, GH22441, GH21789, GH22346)

```
In [1]: s = pd.Series([1, 2, np.nan], dtype='Int64')

In [2]: s
Out[2]:
0       1
1       2
2    <NA>
Length: 3, dtype: Int64
```

Operations on these dtypes will propagate `NaN` as other pandas operations.

```
# arithmetic
In [3]: s + 1
Out[3]:
0       2
1       3
2    <NA>
Length: 3, dtype: Int64

# comparison
In [4]: s == 1
Out[4]:
0     True
1    False
2     <NA>
Length: 3, dtype: boolean

# indexing
In [5]: s.iloc[1:3]
Out[5]:
1       2
2    <NA>
Length: 2, dtype: Int64

# operate with other dtypes
In [6]: s + s.iloc[1:3].astype('Int8')
Out[6]:
0    <NA>
1       4
2    <NA>
Length: 3, dtype: Int64
```

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```
# coerce when needed
In [7]: s + 0.01
Out[7]:
0    1.01
1    2.01
2    <NA>
Length: 3, dtype: Float64
```

These dtypes can operate as part of a `DataFrame`.

```
In [8]: df = pd.DataFrame({'A': s, 'B': [1, 1, 3], 'C': list('aab')})

In [9]: df
Out[9]:
      A  B  C
0     1  1  a
1     2  1  a
2  <NA>  3  b

[3 rows x 3 columns]

In [10]: df.dtypes
Out[10]:
A     Int64
B     int64
C    object
Length: 3, dtype: object
```

These dtypes can be merged, reshaped, and casted.

```
In [11]: pd.concat([df[['A']], df[['B', 'C']]], axis=1).dtypes
Out[11]:
A     Int64
B     int64
C    object
Length: 3, dtype: object

In [12]: df['A'].astype(float)
Out[12]:
0    1.0
1    2.0
2    NaN
Name: A, Length: 3, dtype: float64
```

Reduction and groupby operations such as `sum` work.

```
In [13]: df.sum()
Out[13]:
A      3
B      5
C    aab
Length: 3, dtype: object

In [14]: df.groupby('B').A.sum()
Out[14]:
B
```

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```
1    3
3    0
Name: A, Length: 2, dtype: Int64
```

Warning: The Integer NA support currently uses the capitalized dtype version, e.g. `Int8` as compared to the traditional `int8`. This may be changed at a future date.

See *Nullable integer data type* for more.

Accessing the values in a Series or Index

`Series.array` and *`Index.array`* have been added for extracting the array backing a `Series` or `Index`. (GH19954, GH23623)

```
In [15]: idx = pd.period_range('2000', periods=4)

In [16]: idx.array
Out[16]:
<PeriodArray>
['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04']
Length: 4, dtype: period[D]

In [17]: pd.Series(idx).array
Out[17]:
<PeriodArray>
['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04']
Length: 4, dtype: period[D]
```

Historically, this would have been done with `series.values`, but with `.values` it was unclear whether the returned value would be the actual array, some transformation of it, or one of pandas custom arrays (like `Categorical`). For example, with *`PeriodIndex`*, `.values` generates a new ndarray of period objects each time.

```
In [18]: idx.values
Out[18]:
array([Period('2000-01-01', 'D'), Period('2000-01-02', 'D'),
       Period('2000-01-03', 'D'), Period('2000-01-04', 'D')], dtype=object)

In [19]: id(idx.values)
Out[19]: 140118275352208

In [20]: id(idx.values)
Out[20]: 140117383988688
```

If you need an actual NumPy array, use *`Series.to_numpy()`* or *`Index.to_numpy()`*.

```
In [21]: idx.to_numpy()
Out[21]:
array([Period('2000-01-01', 'D'), Period('2000-01-02', 'D'),
       Period('2000-01-03', 'D'), Period('2000-01-04', 'D')], dtype=object)

In [22]: pd.Series(idx).to_numpy()
```

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```
Out[22]:
array([Period('2000-01-01', 'D'), Period('2000-01-02', 'D'),
       Period('2000-01-03', 'D'), Period('2000-01-04', 'D')], dtype=object)
```

For Series and Indexes backed by normal NumPy arrays, *Series.array* will return a new *arrays.PandasArray*, which is a thin (no-copy) wrapper around a numpy.ndarray. *PandasArray* isn't especially useful on its own, but it does provide the same interface as any extension array defined in pandas or by a third-party library.

```
In [23]: ser = pd.Series([1, 2, 3])

In [24]: ser.array
Out[24]:
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64

In [25]: ser.to_numpy()
Out[25]: array([1, 2, 3])
```

We haven't removed or deprecated *Series.values* or *DataFrame.values*, but we highly recommend and using `.array` or `.to_numpy()` instead.

See *Dtypes* and *Attributes and Underlying Data* for more.

pandas.array: a new top-level method for creating arrays

A new top-level method *array()* has been added for creating 1-dimensional arrays (GH22860). This can be used to create any *extension array*, including extension arrays registered by 3rd party libraries. See the *dtypes docs* for more on extension arrays.

```
In [26]: pd.array([1, 2, np.nan], dtype='Int64')
Out[26]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64

In [27]: pd.array(['a', 'b', 'c'], dtype='category')
Out[27]:
['a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Passing data for which there isn't dedicated extension type (e.g. float, integer, etc.) will return a new *arrays.PandasArray*, which is just a thin (no-copy) wrapper around a numpy.ndarray that satisfies the pandas extension array interface.

```
In [28]: pd.array([1, 2, 3])
Out[28]:
<IntegerArray>
[1, 2, 3]
Length: 3, dtype: Int64
```

On their own, a *PandasArray* isn't a very useful object. But if you need write low-level code that works generically for any *ExtensionArray*, *PandasArray* satisfies that need.

Notice that by default, if no `dtype` is specified, the dtype of the returned array is inferred from the data. In particular, note that the first example of `[1, 2, np.nan]` would have returned a floating-point array, since `NaN` is a float.

```
In [29]: pd.array([1, 2, np.nan])
Out[29]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

Storing Interval and Period data in Series and DataFrame

Interval and *Period* data may now be stored in a *Series* or *DataFrame*, in addition to an *IntervalIndex* and *PeriodIndex* like previously (GH19453, GH22862).

```
In [30]: ser = pd.Series(pd.interval_range(0, 5))

In [31]: ser
Out[31]:
0    (0, 1]
1    (1, 2]
2    (2, 3]
3    (3, 4]
4    (4, 5]
Length: 5, dtype: interval

In [32]: ser.dtype
Out[32]: interval[int64]
```

For periods:

```
In [33]: pser = pd.Series(pd.period_range("2000", freq="D", periods=5))

In [34]: pser
Out[34]:
0    2000-01-01
1    2000-01-02
2    2000-01-03
3    2000-01-04
4    2000-01-05
Length: 5, dtype: period[D]

In [35]: pser.dtype
Out[35]: period[D]
```

Previously, these would be cast to a NumPy array with object dtype. In general, this should result in better performance when storing an array of intervals or periods in a *Series* or column of a *DataFrame*.

Use *Series.array* to extract the underlying array of intervals or periods from the `Series`:

```
In [36]: ser.array
Out[36]:
<IntervalArray>
[(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]]
Length: 5, closed: right, dtype: interval[int64]

In [37]: pser.array
```

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```
Out[37]:
<PeriodArray>
['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04', '2000-01-05']
Length: 5, dtype: period[D]
```

These return an instance of *arrays.IntervalArray* or *arrays.PeriodArray*, the new extension arrays that back interval and period data.

Warning: For backwards compatibility, *Series.values* continues to return a NumPy array of objects for Interval and Period data. We recommend using *Series.array* when you need the array of data stored in the `Series`, and *Series.to_numpy()* when you know you need a NumPy array.

See *Dtypes* and *Attributes and Underlying Data* for more.

Joining with two multi-indexes

DataFrame.merge() and *DataFrame.join()* can now be used to join multi-indexed `Dataframe` instances on the overlapping index levels (GH6360)

See the *Merge, join, and concatenate* documentation section.

```
In [38]: index_left = pd.MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
   ....:                                         ('K1', 'X2')],
   ....:                                        names=['key', 'X'])
   ....:

In [39]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
   ....:                      'B': ['B0', 'B1', 'B2']}, index=index_left)
   ....:

In [40]: index_right = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
   ....:                                          ('K2', 'Y2'), ('K2', 'Y3')],
   ....:                                         names=['key', 'Y'])
   ....:

In [41]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                       'D': ['D0', 'D1', 'D2', 'D3']}, index=index_right)
   ....:

In [42]: left.join(right)
Out[42]:
            A   B   C   D
key X  Y
K0  X0 Y0  A0  B0  C0  D0
    X1 Y0  A1  B1  C0  D0
K1  X2 Y1  A2  B2  C1  D1

[3 rows x 4 columns]
```

For earlier versions this can be done using the following.

```
In [43]: pd.merge(left.reset_index(), right.reset_index(),
   ....:          on=['key'], how='inner').set_index(['key', 'X', 'Y'])
   ....:
```

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```
Out[43]:
             A   B   C   D
key X  Y
K0  X0 Y0   A0  B0  C0  D0
    X1 Y0   A1  B1  C0  D0
K1  X2 Y1   A2  B2  C1  D1

[3 rows x 4 columns]
```

Function `read_html` enhancements

read_html() previously ignored `colspan` and `rowspan` attributes. Now it understands them, treating them as sequences of cells with the same value. (GH17054)

```
In [44]: result = pd.read_html("""
   ....:   <table>
   ....:     <thead>
   ....:       <tr>
   ....:         <th>A</th><th>B</th><th>C</th>
   ....:       </tr>
   ....:     </thead>
   ....:     <tbody>
   ....:       <tr>
   ....:         <td colspan="2">1</td><td>2</td>
   ....:       </tr>
   ....:     </tbody>
   ....:   </table>""")
   ....:
```

Previous behavior:

```
In [13]: result
Out [13]:
[   A  B   C
 0  1  2 NaN]
```

New behavior:

```
In [45]: result
Out[45]:
[   A  B  C
 0  1  1  2

 [1 rows x 3 columns]]
```

New `Styler.pipe()` method

The *Styler* class has gained a *pipe()* method. This provides a convenient way to apply users' predefined styling functions, and can help reduce "boilerplate" when using DataFrame styling functionality repeatedly within a notebook. (GH23229)

```
In [46]: df = pd.DataFrame({'N': [1250, 1500, 1750], 'X': [0.25, 0.35, 0.50]})

In [47]: def format_and_align(styler):
   ....:     return (styler.format({'N': '{:,}', 'X': '{:.1%}'})
   ....:                   .set_properties(**{'text-align': 'right'}))
   ....:

In [48]: df.style.pipe(format_and_align).set_caption('Summary of results.')
Out[48]: <pandas.io.formats.style.Styler at 0x7f7094eb7b20>
```

Similar methods already exist for other classes in pandas, including *DataFrame.pipe()*, *GroupBy.pipe()*, and *Resampler.pipe()*.

Renaming names in a MultiIndex

DataFrame.rename_axis() now supports `index` and `columns` arguments and *Series.rename_axis()* supports `index` argument (GH19978).

This change allows a dictionary to be passed so that some of the names of a `MultiIndex` can be changed.

Example:

```
In [49]: mi = pd.MultiIndex.from_product([list('AB'), list('CD'), list('EF')],
   ....:                                 names=['AB', 'CD', 'EF'])
   ....:

In [50]: df = pd.DataFrame(list(range(len(mi))), index=mi, columns=['N'])

In [51]: df
Out[51]:
           N
AB CD EF
A  C  E    0
      F    1
   D  E    2
      F    3
B  C  E    4
      F    5
   D  E    6
      F    7

[8 rows x 1 columns]

In [52]: df.rename_axis(index={'CD': 'New'})
Out[52]:
            N
AB New EF
A  C   E    0
       F    1
   D   E    2
```

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```
        F   3
B  C    E   4
        F   5
   D    E   6
        F   7

[8 rows x 1 columns]
```

See the *Advanced documentation on renaming* for more details.

Other enhancements

- *merge()* now directly allows merge between objects of type DataFrame and named Series, without the need to convert the Series object into a DataFrame beforehand (GH21220)
- ExcelWriter now accepts mode as a keyword argument, enabling append to existing workbooks when using the openpyxl engine (GH3441)
- FrozenList has gained the .union() and .difference() methods. This functionality greatly simplifies groupby's that rely on explicitly excluding certain columns. See *Splitting an object into groups* for more information (GH15475, GH15506).
- *DataFrame.to_parquet()* now accepts index as an argument, allowing the user to override the engine's default behavior to include or omit the dataframe's indexes from the resulting Parquet file. (GH20768)
- *read_feather()* now accepts columns as an argument, allowing the user to specify which columns should be read. (GH24025)
- *DataFrame.corr()* and *Series.corr()* now accept a callable for generic calculation methods of correlation, e.g. histogram intersection (GH22684)
- *DataFrame.to_string()* now accepts decimal as an argument, allowing the user to specify which decimal separator should be used in the output. (GH23614)
- *DataFrame.to_html()* now accepts render_links as an argument, allowing the user to generate HTML with links to any URLs that appear in the DataFrame. See the *section on writing HTML* in the IO docs for example usage. (GH2679)
- *pandas.read_csv()* now supports pandas extension types as an argument to dtype, allowing the user to use pandas extension types when reading CSVs. (GH23228)
- The *shift()* method now accepts fill_value as an argument, allowing the user to specify a value which will be used instead of NA/NaT in the empty periods. (GH15486)
- *to_datetime()* now supports the %Z and %z directive when passed into format (GH13486)
- *Series.mode()* and *DataFrame.mode()* now support the dropna parameter which can be used to specify whether NaN/NaT values should be considered (GH17534)
- *DataFrame.to_csv()* and *Series.to_csv()* now support the compression keyword when a file handle is passed. (GH21227)
- *Index.droplevel()* is now implemented also for flat indexes, for compatibility with *MultiIndex* (GH21115)
- *Series.droplevel()* and *DataFrame.droplevel()* are now implemented (GH20342)
- Added support for reading from/writing to Google Cloud Storage via the gcsfs library (GH19454, GH23094)

- *DataFrame.to_gbq()* and *read_gbq()* signature and documentation updated to reflect changes from the pandas-gbq library version 0.8.0. Adds a `credentials` argument, which enables the use of any kind of google-auth credentials. (GH21627, GH22557, GH23662)
- New method *HDFStore.walk()* will recursively walk the group hierarchy of an HDF5 file (GH10932)
- *read_html()* copies cell data across `colspan` and `rowspan`, and it treats all-`th` table rows as headers if `header` kwarg is not given and there is no `thead` (GH17054)
- *Series.nlargest()*, *Series.nsmallest()*, *DataFrame.nlargest()*, and *DataFrame.nsmallest()* now accept the value `"all"` for the `keep` argument. This keeps all ties for the nth largest/smallest value (GH16818)
- *IntervalIndex* has gained the *set_closed()* method to change the existing `closed` value (GH21670)
- *to_csv()*, *to_csv()*, *to_json()*, and *to_json()* now support `compression='infer'` to infer compression based on filename extension (GH15008). The default compression for `to_csv`, `to_json`, and `to_pickle` methods has been updated to `'infer'` (GH22004).
- *DataFrame.to_sql()* now supports writing `TIMESTAMP WITH TIME ZONE` types for supported databases. For databases that don't support timezones, datetime data will be stored as timezone unaware local timestamps. See the *Datetime data types* for implications (GH9086).
- *to_timedelta()* now supports iso-formatted timedelta strings (GH21877)
- *Series* and *DataFrame* now support `Iterable` objects in the constructor (GH2193)
- *DatetimeIndex* has gained the *DatetimeIndex.timetz* attribute. This returns the local time with timezone information. (GH21358)
- *round()*, *ceil()*, and *floor()* for *DatetimeIndex* and *Timestamp* now support an `ambiguous` argument for handling datetimes that are rounded to ambiguous times (GH18946) and a `nonexistent` argument for handling datetimes that are rounded to nonexistent times. See *Nonexistent times when localizing* (GH22647)
- The result of *resample()* is now iterable similar to `groupby()` (GH15314).
- *Series.resample()* and *DataFrame.resample()* have gained the *pandas.core.resample.Resampler.quantile()* (GH15023).
- *DataFrame.resample()* and *Series.resample()* with a *PeriodIndex* will now respect the `base` argument in the same fashion as with a *DatetimeIndex*. (GH23882)
- *pandas.api.types.is_list_like()* has gained a keyword `allow_sets` which is `True` by default; if `False`, all instances of `set` will not be considered "list-like" anymore (GH23061)
- *Index.to_frame()* now supports overriding column name(s) (GH22580).
- *Categorical.from_codes()* now can take a `dtype` parameter as an alternative to passing `categories` and `ordered` (GH24398).
- New attribute `__git_version__` will return git commit sha of current build (GH21295).
- Compatibility with Matplotlib 3.0 (GH22790).
- Added *Interval.overlaps()*, *arrays.IntervalArray.overlaps()*, and *IntervalIndex.overlaps()* for determining overlaps between interval-like objects (GH21998)
- *read_fwf()* now accepts keyword `infer_nrows` (GH15138).
- *to_parquet()* now supports writing a `DataFrame` as a directory of parquet files partitioned by a subset of the columns when `engine = 'pyarrow'` (GH23283)

- *Timestamp.tz_localize()*, *DatetimeIndex.tz_localize()*, and *Series.tz_localize()* have gained the `nonexistent` argument for alternative handling of nonexistent times. See *Nonexistent times when localizing* (GH8917, GH24466)
- *Index.difference()*, *Index.intersection()*, *Index.union()*, and *Index.symmetric_difference()* now have an optional `sort` parameter to control whether the results should be sorted if possible (GH17839, GH24471)
- *read_excel()* now accepts `usecols` as a list of column names or callable (GH18273)
- *MultiIndex.to_flat_index()* has been added to flatten multiple levels into a single-level *Index* object.
- *DataFrame.to_stata()* and `pandas.io.stata.StataWriter117` can write mixed string columns to Stata strl format (GH23633)
- *DataFrame.between_time()* and *DataFrame.at_time()* have gained the `axis` parameter (GH8839)
- *DataFrame.to_records()* now accepts `index_dtypes` and `column_dtypes` parameters to allow different data types in stored column and index records (GH18146)
- *IntervalIndex* has gained the *is_overlapping* attribute to indicate if the `IntervalIndex` contains any overlapping intervals (GH23309)
- *pandas.DataFrame.to_sql()* has gained the `method` argument to control SQL insertion clause. See the *insertion method* section in the documentation. (GH8953)
- *DataFrame.corrwith()* now supports Spearman's rank correlation, Kendall's tau as well as callable correlation methods. (GH21925)
- *DataFrame.to_json()*, *DataFrame.to_csv()*, *DataFrame.to_pickle()*, and other export methods now support tilde(~) in path argument. (GH23473)

Backwards incompatible API changes

pandas 0.24.0 includes a number of API breaking changes.

Increased minimum versions for dependencies

We have updated our minimum supported versions of dependencies (GH21242, GH18742, GH23774, GH24767). If installed, we now require:

Package	Minimum Version	Required
numpy	1.12.0	X
bottleneck	1.2.0	
fastparquet	0.2.1	
matplotlib	2.0.0	
numexpr	2.6.1	
pandas-gbq	0.8.0	
pyarrow	0.9.0	
pytables	3.4.2	
scipy	0.18.1	
xlrd	1.0.0	
pytest (dev)	3.6	

Additionally we no longer depend on `feather-format` for feather based storage and replaced it with references to `pyarrow` (GH21639 and GH23053).

`os.linesep` is used for `line_terminator` of `DataFrame.to_csv`

`DataFrame.to_csv()` now uses `os.linesep()` rather than `'\n'` for the default line terminator (GH20353). This change only affects when running on Windows, where `'\r\n'` was used for line terminator even when `'\n'` was passed in `line_terminator`.

Previous behavior on Windows:

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],
   ...:                      "string_with_crlf": ["a\r\nbc"]})

In [2]: # When passing file PATH to to_csv,
   ...: # line_terminator does not work, and csv is saved with '\r\n'.
   ...: # Also, this converts all '\n's in the data to '\r\n'.
   ...: data.to_csv("test.csv", index=False, line_terminator='\n')

In [3]: with open("test.csv", mode='rb') as f:
   ...:     print(f.read())
Out[3]: b'string_with_lf,string_with_crlf\r\n"a\r\nbc","a\r\r\nbc"\r\n'

In [4]: # When passing file OBJECT with newline option to
   ...: # to_csv, line_terminator works.
   ...: with open("test2.csv", mode='w', newline='\n') as f:
   ...:     data.to_csv(f, index=False, line_terminator='\n')

In [5]: with open("test2.csv", mode='rb') as f:
   ...:     print(f.read())
Out[5]: b'string_with_lf,string_with_crlf\n"a\nbc","a\r\nbc"\n'
```

New behavior on Windows:

Passing `line_terminator` explicitly, set the `line terminator` to that character.

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],
   ...:                      "string_with_crlf": ["a\r\nbc"]})

In [2]: data.to_csv("test.csv", index=False, line_terminator='\n')

In [3]: with open("test.csv", mode='rb') as f:
   ...:     print(f.read())
Out[3]: b'string_with_lf,string_with_crlf\n"a\nbc","a\r\nbc"\n'
```

On Windows, the value of `os.linesep` is `'\r\n'`, so if `line_terminator` is not set, `'\r\n'` is used for line terminator.

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],
   ...:                      "string_with_crlf": ["a\r\nbc"]})

In [2]: data.to_csv("test.csv", index=False)

In [3]: with open("test.csv", mode='rb') as f:
   ...:     print(f.read())
Out[3]: b'string_with_lf,string_with_crlf\r\n"a\nbc","a\r\nbc"\r\n'
```

For file objects, specifying `newline` is not sufficient to set the line terminator. You must pass in the `line_terminator` explicitly, even in this case.

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],
   ...:                      "string_with_crlf": ["a\r\nbc"]})

In [2]: with open("test2.csv", mode='w', newline='\n') as f:
   ...:     data.to_csv(f, index=False)

In [3]: with open("test2.csv", mode='rb') as f:
   ...:     print(f.read())
Out[3]: b'string_with_lf,string_with_crlf\r\n"a\nbc","a\r\nbc"\r\n'
```

Proper handling of `np.NaN` in a string data-typed column with the Python engine

There was bug in *read_excel()* and *read_csv()* with the Python engine, where missing values turned to `'nan'` with `dtype=str` and `na_filter=True`. Now, these missing values are converted to the string missing indicator, `np.nan`. (GH20377)

Previous behavior:

```
In [5]: data = 'a,b,c\n1,,3\n4,5,6'
In [6]: df = pd.read_csv(StringIO(data), engine='python', dtype=str, na_filter=True)
In [7]: df.loc[0, 'b']
Out[7]:
'nan'
```

New behavior:

```
In [53]: data = 'a,b,c\n1,,3\n4,5,6'

In [54]: df = pd.read_csv(StringIO(data), engine='python', dtype=str, na_filter=True)

In [55]: df.loc[0, 'b']
Out[55]: nan
```

Notice how we now instead output `np.nan` itself instead of a stringified form of it.

Parsing datetime strings with timezone offsets

Previously, parsing datetime strings with UTC offsets with *to_datetime()* or *DatetimeIndex* would automatically convert the datetime to UTC without timezone localization. This is inconsistent from parsing the same datetime string with *Timestamp* which would preserve the UTC offset in the `tz` attribute. Now, *to_datetime()* preserves the UTC offset in the `tz` attribute when all the datetime strings have the same UTC offset (GH17697, GH11736, GH22457)

Previous behavior:

```
In [2]: pd.to_datetime("2015-11-18 15:30:00+05:30")
Out[2]: Timestamp('2015-11-18 10:00:00')

In [3]: pd.Timestamp("2015-11-18 15:30:00+05:30")
Out[3]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')

# Different UTC offsets would automatically convert the datetimes to UTC (without a␣
↪UTC timezone)
```

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```
In [4]: pd.to_datetime(["2015-11-18 15:30:00+05:30", "2015-11-18 16:30:00+06:30"])
Out[4]: DatetimeIndex(['2015-11-18 10:00:00', '2015-11-18 10:00:00'], dtype=
↪'datetime64[ns]', freq=None)
```

New behavior:

```
In [56]: pd.to_datetime("2015-11-18 15:30:00+05:30")
Out[56]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')

In [57]: pd.Timestamp("2015-11-18 15:30:00+05:30")
Out[57]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')
```

Parsing datetime strings with the same UTC offset will preserve the UTC offset in the `tz`

```
In [58]: pd.to_datetime(["2015-11-18 15:30:00+05:30"] * 2)
Out[58]: DatetimeIndex(['2015-11-18 15:30:00+05:30', '2015-11-18 15:30:00+05:30'],␣
↪dtype='datetime64[ns, pytz.FixedOffset(330)]', freq=None)
```

Parsing datetime strings with different UTC offsets will now create an Index of `datetime.datetime` objects with different UTC offsets

```
In [59]: idx = pd.to_datetime(["2015-11-18 15:30:00+05:30",
   ....:                       "2015-11-18 16:30:00+06:30"])
   ....:

In [60]: idx
Out[60]: Index([2015-11-18 15:30:00+05:30, 2015-11-18 16:30:00+06:30], dtype='object')

In [61]: idx[0]
Out[61]: datetime.datetime(2015, 11, 18, 15, 30, tzinfo=tzoffset(None, 19800))

In [62]: idx[1]
Out[62]: datetime.datetime(2015, 11, 18, 16, 30, tzinfo=tzoffset(None, 23400))
```

Passing `utc=True` will mimic the previous behavior but will correctly indicate that the dates have been converted to UTC

```
In [63]: pd.to_datetime(["2015-11-18 15:30:00+05:30",
   ....:                 "2015-11-18 16:30:00+06:30"], utc=True)
   ....:
Out[63]: DatetimeIndex(['2015-11-18 10:00:00+00:00', '2015-11-18 10:00:00+00:00'],␣
↪dtype='datetime64[ns, UTC]', freq=None)
```

Parsing mixed-timezones with `read_csv()`

`read_csv()` no longer silently converts mixed-timezone columns to UTC (GH24987).

Previous behavior

```
>>> import io
>>> content = """\
... a
... 2000-01-01T00:00:00+05:00
... 2000-01-01T00:00:00+06:00"""
>>> df = pd.read_csv(io.StringIO(content), parse_dates=['a'])
```

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```
>>> df.a
0   1999-12-31 19:00:00
1   1999-12-31 18:00:00
Name: a, dtype: datetime64[ns]
```

New behavior

```
In [64]: import io

In [65]: content = """\
   ....: a
   ....: 2000-01-01T00:00:00+05:00
   ....: 2000-01-01T00:00:00+06:00"""
   ....:

In [66]: df = pd.read_csv(io.StringIO(content), parse_dates=['a'])

In [67]: df.a
Out[67]:
0    2000-01-01 00:00:00+05:00
1    2000-01-01 00:00:00+06:00
Name: a, Length: 2, dtype: object
```

As can be seen, the `dtype` is object; each value in the column is a string. To convert the strings to an array of datetimes, the `date_parser` argument

```
In [68]: df = pd.read_csv(io.StringIO(content), parse_dates=['a'],
   ....:                  date_parser=lambda col: pd.to_datetime(col, utc=True))
   ....:

In [69]: df.a
Out[69]:
0   1999-12-31 19:00:00+00:00
1   1999-12-31 18:00:00+00:00
Name: a, Length: 2, dtype: datetime64[ns, UTC]
```

See *Parsing datetime strings with timezone offsets* for more.

Time values in `dt.end_time` and `to_timestamp(how='end')`

The time values in *Period* and *PeriodIndex* objects are now set to '23:59:59.999999999' when calling *Series.dt.end_time*, *Period.end_time*, *PeriodIndex.end_time*, *Period.to_timestamp()* with `how='end'`, or *PeriodIndex.to_timestamp()* with `how='end'` (GH17157)

Previous behavior:

```
In [2]: p = pd.Period('2017-01-01', 'D')
In [3]: pi = pd.PeriodIndex([p])

In [4]: pd.Series(pi).dt.end_time[0]
Out[4]: Timestamp(2017-01-01 00:00:00)

In [5]: p.end_time
Out[5]: Timestamp(2017-01-01 23:59:59.999999999)
```

New behavior:

Calling *Series.dt.end_time* will now result in a time of '23:59:59.999999999' as is the case with *Period.end_time*, for example

```
In [70]: p = pd.Period('2017-01-01', 'D')

In [71]: pi = pd.PeriodIndex([p])

In [72]: pd.Series(pi).dt.end_time[0]
Out[72]: Timestamp('2017-01-01 23:59:59.999999999')

In [73]: p.end_time
Out[73]: Timestamp('2017-01-01 23:59:59.999999999')
```

Series.unique for timezone-aware data

The return type of *Series.unique()* for datetime with timezone values has changed from an numpy.ndarray of *Timestamp* objects to a *arrays.DatetimeArray* (GH24024).

```
In [74]: ser = pd.Series([pd.Timestamp('2000', tz='UTC'),
   ....:                  pd.Timestamp('2000', tz='UTC')])
   ....:
```

Previous behavior:

```
In [3]: ser.unique()
Out[3]: array([Timestamp('2000-01-01 00:00:00+0000', tz='UTC')], dtype=object)
```

New behavior:

```
In [75]: ser.unique()
Out[75]:
<DatetimeArray>
['2000-01-01 00:00:00+00:00']
Length: 1, dtype: datetime64[ns, UTC]
```

Sparse data structure refactor

SparseArray, the array backing SparseSeries and the columns in a SparseDataFrame, is now an extension array (GH21978, GH19056, GH22835). To conform to this interface and for consistency with the rest of pandas, some API breaking changes were made:

- SparseArray is no longer a subclass of numpy.ndarray. To convert a SparseArray to a NumPy array, use numpy.asarray().
- SparseArray.dtype and SparseSeries.dtype are now instances of *SparseDtype*, rather than np.dtype. Access the underlying dtype with SparseDtype.subtype.
- numpy.asarray(sparse_array) now returns a dense array with all the values, not just the non-fill-value values (GH14167)
- SparseArray.take now matches the API of *pandas.api.extensions.ExtensionArray.take()* (GH19506):
  - The default value of allow_fill has changed from False to True.
  - The out and mode parameters are now longer accepted (previously, this raised if they were specified).

  - Passing a scalar for `indices` is no longer allowed.

- The result of *`concat()`* with a mix of sparse and dense Series is a Series with sparse values, rather than a `SparseSeries`.
- `SparseDataFrame.combine` and `DataFrame.combine_first` no longer supports combining a sparse column with a dense column while preserving the sparse subtype. The result will be an object-dtype SparseArray.
- Setting `SparseArray.fill_value` to a fill value with a different dtype is now allowed.
- `DataFrame[column]` is now a *`Series`* with sparse values, rather than a `SparseSeries`, when slicing a single column with sparse values (GH23559).
- The result of *`Series.where()`* is now a `Series` with sparse values, like with other extension arrays (GH24077)

Some new warnings are issued for operations that require or are likely to materialize a large dense array:

- A *`errors.PerformanceWarning`* is issued when using fillna with a `method`, as a dense array is constructed to create the filled array. Filling with a `value` is the efficient way to fill a sparse array.
- A *`errors.PerformanceWarning`* is now issued when concatenating sparse Series with differing fill values. The fill value from the first sparse array continues to be used.

In addition to these API breaking changes, many *Performance Improvements and Bug Fixes have been made*.

Finally, a `Series.sparse` accessor was added to provide sparse-specific methods like *`Series.sparse.from_coo()`*.

```
In [76]: s = pd.Series([0, 0, 1, 1, 1], dtype='Sparse[int]')

In [77]: s.sparse.density
Out[77]: 0.6
```

`get_dummies()` always returns a DataFrame

Previously, when `sparse=True` was passed to *`get_dummies()`*, the return value could be either a *`DataFrame`* or a `SparseDataFrame`, depending on whether all or a just a subset of the columns were dummy-encoded. Now, a *`DataFrame`* is always returned (GH24284).

Previous behavior

The first *`get_dummies()`* returns a *`DataFrame`* because the column `A` is not dummy encoded. When just `["B", "C"]` are passed to `get_dummies`, then all the columns are dummy-encoded, and a `SparseDataFrame` was returned.

```
In [2]: df = pd.DataFrame({"A": [1, 2], "B": ['a', 'b'], "C": ['a', 'a']})

In [3]: type(pd.get_dummies(df, sparse=True))
Out[3]: pandas.core.frame.DataFrame

In [4]: type(pd.get_dummies(df[['B', 'C']], sparse=True))
Out[4]: pandas.core.sparse.frame.SparseDataFrame
```

New behavior

Now, the return type is consistently a *`DataFrame`*.

```
In [78]: type(pd.get_dummies(df, sparse=True))
Out[78]: pandas.core.frame.DataFrame

In [79]: type(pd.get_dummies(df[['B', 'C']], sparse=True))
Out[79]: pandas.core.frame.DataFrame
```

Note: There's no difference in memory usage between a `SparseDataFrame` and a *DataFrame* with sparse values. The memory usage will be the same as in the previous version of pandas.

Raise ValueError in `DataFrame.to_dict(orient='index')`

Bug in *DataFrame.to_dict()* raises `ValueError` when used with `orient='index'` and a non-unique index instead of losing data (GH22801)

```
In [80]: df = pd.DataFrame({'a': [1, 2], 'b': [0.5, 0.75]}, index=['A', 'A'])

In [81]: df
Out[81]:
   a     b
A  1  0.50
A  2  0.75

[2 rows x 2 columns]

In [82]: df.to_dict(orient='index')
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-82-f5309a7c6adb> in <module>
----> 1 df.to_dict(orient='index')

/pandas/pandas/core/frame.py in to_dict(self, orient, into)
   1605         elif orient == "index":
   1606             if not self.index.is_unique:
-> 1607                 raise ValueError("DataFrame index must be unique for orient=
↪'index'.")
   1608             return into_c(
   1609                 (t[0], dict(zip(self.columns, t[1:]))))

ValueError: DataFrame index must be unique for orient='index'.
```

Tick DateOffset normalize restrictions

Creating a `Tick` object (`Day`, `Hour`, `Minute`, `Second`, `Milli`, `Micro`, `Nano`) with `normalize=True` is no longer supported. This prevents unexpected behavior where addition could fail to be monotone or associative. (GH21427)

Previous behavior:

```
In [2]: ts = pd.Timestamp('2018-06-11 18:01:14')

In [3]: ts
Out[3]: Timestamp('2018-06-11 18:01:14')
```

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```
In [4]: tic = pd.offsets.Hour(n=2, normalize=True)
   ...:

In [5]: tic
Out[5]: <2 * Hours>

In [6]: ts + tic
Out[6]: Timestamp('2018-06-11 00:00:00')

In [7]: ts + tic + tic + tic == ts + (tic + tic + tic)
Out[7]: False
```

New behavior:

```
In [83]: ts = pd.Timestamp('2018-06-11 18:01:14')

In [84]: tic = pd.offsets.Hour(n=2)

In [85]: ts + tic + tic + tic == ts + (tic + tic + tic)
Out[85]: True
```

Period subtraction

Subtraction of a `Period` from another `Period` will give a `DateOffset`. instead of an integer (GH21314)

Previous behavior:

```
In [2]: june = pd.Period('June 2018')

In [3]: april = pd.Period('April 2018')

In [4]: june - april
Out [4]: 2
```

New behavior:

```
In [86]: june = pd.Period('June 2018')

In [87]: april = pd.Period('April 2018')

In [88]: june - april
Out[88]: <2 * MonthEnds>
```

Similarly, subtraction of a `Period` from a `PeriodIndex` will now return an `Index` of `DateOffset` objects instead of an `Int64Index`

Previous behavior:

```
In [2]: pi = pd.period_range('June 2018', freq='M', periods=3)

In [3]: pi - pi[0]
Out[3]: Int64Index([0, 1, 2], dtype='int64')
```

New behavior:

```
In [89]: pi = pd.period_range('June 2018', freq='M', periods=3)

In [90]: pi - pi[0]
Out[90]: Index([<0 * MonthEnds>, <MonthEnd>, <2 * MonthEnds>], dtype='object')
```

Addition/subtraction of `NaN` from `DataFrame`

Adding or subtracting `NaN` from a *`DataFrame`* column with `timedelta64[ns]` dtype will now raise a `TypeError` instead of returning all-`NaT`. This is for compatibility with `TimedeltaIndex` and `Series` behavior (GH22163)

```
In [91]: df = pd.DataFrame([pd.Timedelta(days=1)])

In [92]: df
Out[92]:
       0
0 1 days

[1 rows x 1 columns]
```

Previous behavior:

```
In [4]: df = pd.DataFrame([pd.Timedelta(days=1)])

In [5]: df - np.nan
Out[5]:
    0
0 NaT
```

New behavior:

```
In [2]: df - np.nan
...
TypeError: unsupported operand type(s) for -: 'TimedeltaIndex' and 'float'
```

DataFrame comparison operations broadcasting changes

Previously, the broadcasting behavior of *`DataFrame`* comparison operations (==, !=, ...) was inconsistent with the behavior of arithmetic operations (+, -, ...). The behavior of the comparison operations has been changed to match the arithmetic operations in these cases. (GH22880)

The affected cases are:

- operating against a 2-dimensional `np.ndarray` with either 1 row or 1 column will now broadcast the same way a `np.ndarray` would (GH23000).
- a list or tuple with length matching the number of rows in the *`DataFrame`* will now raise `ValueError` instead of operating column-by-column (GH22880.
- a list or tuple with length matching the number of columns in the *`DataFrame`* will now operate row-by-row instead of raising `ValueError` (GH22880).

```
In [93]: arr = np.arange(6).reshape(3, 2)
```

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```
In [94]: df = pd.DataFrame(arr)

In [95]: df
Out[95]:
   0  1
0  0  1
1  2  3
2  4  5

[3 rows x 2 columns]
```

Previous behavior:

```
In [5]: df == arr[[0], :]
    ...: # comparison previously broadcast where arithmetic would raise
Out[5]:
       0      1
0   True   True
1  False  False
2  False  False
In [6]: df + arr[[0], :]
...
ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (1, 2)

In [7]: df == (1, 2)
    ...: # length matches number of columns;
    ...: # comparison previously raised where arithmetic would broadcast
...
ValueError: Invalid broadcasting comparison [(1, 2)] with block values
In [8]: df + (1, 2)
Out[8]:
   0  1
0  1  3
1  3  5
2  5  7

In [9]: df == (1, 2, 3)
    ...:  # length matches number of rows
    ...:  # comparison previously broadcast where arithmetic would raise
Out[9]:
       0      1
0  False   True
1   True  False
2  False  False
In [10]: df + (1, 2, 3)
...
ValueError: Unable to coerce to Series, length must be 2: given 3
```

New behavior:

```
# Comparison operations and arithmetic operations both broadcast.
In [96]: df == arr[[0], :]
Out[96]:
       0      1
0   True   True
1  False  False
2  False  False
```

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```
[3 rows x 2 columns]

In [97]: df + arr[[0], :]
Out[97]:
   0  1
0  0  2
1  2  4
2  4  6

[3 rows x 2 columns]
```

```
# Comparison operations and arithmetic operations both broadcast.
In [98]: df == (1, 2)
Out[98]:
       0      1
0  False  False
1  False  False
2  False  False

[3 rows x 2 columns]

In [99]: df + (1, 2)
Out[99]:
   0  1
0  1  3
1  3  5
2  5  7

[3 rows x 2 columns]
```

```
# Comparison operations and arithmetic operations both raise ValueError.
In [6]: df == (1, 2, 3)
...
ValueError: Unable to coerce to Series, length must be 2: given 3

In [7]: df + (1, 2, 3)
...
ValueError: Unable to coerce to Series, length must be 2: given 3
```

DataFrame arithmetic operations broadcasting changes

DataFrame arithmetic operations when operating with 2-dimensional `np.ndarray` objects now broadcast in the same way as `np.ndarray` broadcast. (GH23000)

```
In [100]: arr = np.arange(6).reshape(3, 2)

In [101]: df = pd.DataFrame(arr)

In [102]: df
Out[102]:
   0  1
0  0  1
1  2  3
```

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```
2  4  5

[3 rows x 2 columns]
```

Previous behavior:

```
In [5]: df + arr[[0], :]   # 1 row, 2 columns
...
ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (1, 2)
In [6]: df + arr[:, [1]]   # 1 column, 3 rows
...
ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (3, 1)
```

New behavior:

```
In [103]: df + arr[[0], :]   # 1 row, 2 columns
Out[103]:
   0  1
0  0  2
1  2  4
2  4  6

[3 rows x 2 columns]

In [104]: df + arr[:, [1]]   # 1 column, 3 rows
Out[104]:
   0   1
0  1   2
1  5   6
2  9  10

[3 rows x 2 columns]
```

Series and Index data-dtype incompatibilities

`Series` and `Index` constructors now raise when the data is incompatible with a passed `dtype=` (GH15832)

Previous behavior:

```
In [4]: pd.Series([-1], dtype="uint64")
Out [4]:
0    18446744073709551615
dtype: uint64
```

New behavior:

```
In [4]: pd.Series([-1], dtype="uint64")
Out [4]:
...
OverflowError: Trying to coerce negative values to unsigned integers
```

Concatenation changes

Calling *pandas.concat()* on a Categorical of ints with NA values now causes them to be processed as objects when concatenating with anything other than another Categorical of ints (GH19214)

```
In [105]: s = pd.Series([0, 1, np.nan])

In [106]: c = pd.Series([0, 1, np.nan], dtype="category")
```

Previous behavior

```
In [3]: pd.concat([s, c])
Out[3]:
0    0.0
1    1.0
2    NaN
0    0.0
1    1.0
2    NaN
dtype: float64
```

New behavior

```
In [107]: pd.concat([s, c])
Out[107]:
0    0.0
1    1.0
2    NaN
0    0.0
1    1.0
2    NaN
Length: 6, dtype: float64
```

Datetimelike API changes

- For *DatetimeIndex* and *TimedeltaIndex* with non-None freq attribute, addition or subtraction of integer-dtyped array or Index will return an object of the same class (GH19959)
- DateOffset objects are now immutable. Attempting to alter one of these will now raise AttributeError (GH21341)
- *PeriodIndex* subtraction of another PeriodIndex will now return an object-dtype *Index* of DateOffset objects instead of raising a TypeError (GH20049)
- *cut()* and *qcut()* now returns a *DatetimeIndex* or *TimedeltaIndex* bins when the input is datetime or timedelta dtype respectively and retbins=True (GH19891)
- *DatetimeIndex.to_period()* and *Timestamp.to_period()* will issue a warning when timezone information will be lost (GH21333)
- PeriodIndex.tz_convert() and PeriodIndex.tz_localize() have been removed (GH21781)

Other API changes

- A newly constructed empty *DataFrame* with integer as the `dtype` will now only be cast to `float64` if `index` is specified (GH22858)
- *Series.str.cat()* will now raise if `others` is a `set` (GH23009)
- Passing scalar values to *DatetimeIndex* or *TimedeltaIndex* will now raise `TypeError` instead of `ValueError` (GH23539)
- `max_rows` and `max_cols` parameters removed from `HTMLFormatter` since truncation is handled by `DataFrameFormatter` (GH23818)
- *read_csv()* will now raise a `ValueError` if a column with missing values is declared as having dtype `bool` (GH20591)
- The column order of the resultant *DataFrame* from *MultiIndex.to_frame()* is now guaranteed to match the *MultiIndex.names* order. (GH22420)
- Incorrectly passing a *DatetimeIndex* to *MultiIndex.from_tuples()*, rather than a sequence of tuples, now raises a `TypeError` rather than a `ValueError` (GH24024)
- `pd.offsets.generate_range()` argument `time_rule` has been removed; use `offset` instead (GH24157)
- In 0.23.x, pandas would raise a `ValueError` on a merge of a numeric column (e.g. `int` dtyped column) and an `object` dtyped column (GH9780). We have re-enabled the ability to merge `object` and other dtypes; pandas will still raise on a merge between a numeric and an `object` dtyped column that is composed only of strings (GH21681)
- Accessing a level of a `MultiIndex` with a duplicate name (e.g. in *get_level_values()*) now raises a `ValueError` instead of a `KeyError` (GH21678).
- Invalid construction of `IntervalDtype` will now always raise a `TypeError` rather than a `ValueError` if the subdtype is invalid (GH21185)
- Trying to reindex a `DataFrame` with a non unique `MultiIndex` now raises a `ValueError` instead of an `Exception` (GH21770)
- *Index* subtraction will attempt to operate element-wise instead of raising `TypeError` (GH19369)
- *pandas.io.formats.style.Styler* supports a `number-format` property when using *to_excel()* (GH22015)
- *DataFrame.corr()* and *Series.corr()* now raise a `ValueError` along with a helpful error message instead of a `KeyError` when supplied with an invalid method (GH22298)
- `shift()` will now always return a copy, instead of the previous behaviour of returning self when shifting by 0 (GH22397)
- *DataFrame.set_index()* now gives a better (and less frequent) KeyError, raises a `ValueError` for incorrect types, and will not fail on duplicate column names with `drop=True`. (GH22484)
- Slicing a single row of a DataFrame with multiple ExtensionArrays of the same type now preserves the dtype, rather than coercing to object (GH22784)
- `DateOffset` attribute `_cacheable` and method `_should_cache` have been removed (GH23118)
- *Series.searchsorted()*, when supplied a scalar value to search for, now returns a scalar instead of an array (GH23801).
- `Categorical.searchsorted()`, when supplied a scalar value to search for, now returns a scalar instead of an array (GH23466).

- `Categorical.searchsorted()` now raises a `KeyError` rather that a `ValueError`, if a searched for key is not found in its categories (GH23466).
- *`Index.hasnans()`* and *`Series.hasnans()`* now always return a python boolean. Previously, a python or a numpy boolean could be returned, depending on circumstances (GH23294).
- The order of the arguments of *`DataFrame.to_html()`* and *`DataFrame.to_string()`* is rearranged to be consistent with each other. (GH23614)
- `CategoricalIndex.reindex()` now raises a `ValueError` if the target index is non-unique and not equal to the current index. It previously only raised if the target index was not of a categorical dtype (GH23963).
- *`Series.to_list()`* and *`Index.to_list()`* are now aliases of `Series.tolist` respectively `Index.tolist` (GH8826)
- The result of `SparseSeries.unstack` is now a *`DataFrame`* with sparse values, rather than a `SparseDataFrame` (GH24372).
- *`DatetimeIndex`* and *`TimedeltaIndex`* no longer ignore the dtype precision. Passing a non-nanosecond resolution dtype will raise a `ValueError` (GH24753)

Extension type changes

Equality and hashability

pandas now requires that extension dtypes be hashable (i.e. the respective `ExtensionDtype` objects; hashability is not a requirement for the values of the corresponding `ExtensionArray`). The base class implements a default `__eq__` and `__hash__`. If you have a parametrized dtype, you should update the `ExtensionDtype._metadata` tuple to match the signature of your `__init__` method. See *`pandas.api.extensions.ExtensionDtype`* for more (GH22476).

New and changed methods

- `dropna()` has been added (GH21185)
- `repeat()` has been added (GH24349)
- The `ExtensionArray` constructor, `_from_sequence` now take the keyword arg `copy=False` (GH21185)
- *`pandas.api.extensions.ExtensionArray.shift()`* added as part of the basic `ExtensionArray` interface (GH22387).
- `searchsorted()` has been added (GH24350)
- Support for reduction operations such as `sum`, `mean` via opt-in base class method override (GH22762)
- `ExtensionArray.isna()` is allowed to return an `ExtensionArray` (GH22325).

Dtype changes

- `ExtensionDtype` has gained the ability to instantiate from string dtypes, e.g. `decimal` would instantiate a registered `DecimalDtype`; furthermore the `ExtensionDtype` has gained the method `construct_array_type` (GH21185)
- Added `ExtensionDtype._is_numeric` for controlling whether an extension dtype is considered numeric (GH22290).
- Added `pandas.api.types.register_extension_dtype()` to register an extension type with pandas (GH22664)
- Updated the `.type` attribute for `PeriodDtype`, `DatetimeTZDtype`, and `IntervalDtype` to be instances of the dtype (`Period`, `Timestamp`, and `Interval` respectively) (GH22938)

Operator support

A `Series` based on an `ExtensionArray` now supports arithmetic and comparison operators (GH19577). There are two approaches for providing operator support for an `ExtensionArray`:

1. Define each of the operators on your `ExtensionArray` subclass.
2. Use an operator implementation from pandas that depends on operators that are already defined on the underlying elements (scalars) of the `ExtensionArray`.

See the *ExtensionArray Operator Support* documentation section for details on both ways of adding operator support.

Other changes

- A default repr for *pandas.api.extensions.ExtensionArray* is now provided (GH23601).
- `ExtensionArray._formatting_values()` is deprecated. Use `ExtensionArray._formatter` instead. (GH23601)
- An `ExtensionArray` with a boolean dtype now works correctly as a boolean indexer. *pandas.api.types.is_bool_dtype()* now properly considers them boolean (GH22326)

Bug fixes

- Bug in *Series.get()* for `Series` using `ExtensionArray` and integer index (GH21257)
- *shift()* now dispatches to `ExtensionArray.shift()` (GH22386)
- *Series.combine()* works correctly with *ExtensionArray* inside of *Series* (GH20825)
- *Series.combine()* with scalar argument now works for any function type (GH21248)
- *Series.astype()* and *DataFrame.astype()* now dispatch to `ExtensionArray.astype()` (GH21185).
- Slicing a single row of a `DataFrame` with multiple ExtensionArrays of the same type now preserves the dtype, rather than coercing to object (GH22784)
- Bug when concatenating multiple `Series` with different extension dtypes not casting to object dtype (GH22994)
- Series backed by an `ExtensionArray` now work with *util.hash_pandas_object()* (GH23066)
- *DataFrame.stack()* no longer converts to object dtype for DataFrames where each column has the same extension dtype. The output Series will have the same dtype as the columns (GH23077).
- *Series.unstack()* and *DataFrame.unstack()* no longer convert extension arrays to object-dtype ndarrays. Each column in the output `DataFrame` will now have the same dtype as the input (GH23077).
- Bug when grouping `Dataframe.groupby()` and aggregating on `ExtensionArray` it was not returning the actual `ExtensionArray` dtype (GH23227).
- Bug in *pandas.merge()* when merging on an extension array-backed column (GH23020).

Deprecations

- `MultiIndex.labels` has been deprecated and replaced by *`MultiIndex.codes`*. The functionality is unchanged. The new name better reflects the natures of these codes and makes the `MultiIndex` API more similar to the API for *`CategoricalIndex`* (GH13443). As a consequence, other uses of the name `labels` in `MultiIndex` have also been deprecated and replaced with `codes`:
  - You should initialize a `MultiIndex` instance using a parameter named `codes` rather than `labels`.
  - `MultiIndex.set_labels` has been deprecated in favor of *`MultiIndex.set_codes()`*.
  - For method `MultiIndex.copy()`, the `labels` parameter has been deprecated and replaced by a `codes` parameter.
- *`DataFrame.to_stata()`*, *`read_stata()`*, `StataReader` and `StataWriter` have deprecated the `encoding` argument. The encoding of a Stata dta file is determined by the file type and cannot be changed (GH21244)
- `MultiIndex.to_hierarchical()` is deprecated and will be removed in a future version (GH21613)
- `Series.ptp()` is deprecated. Use `numpy.ptp` instead (GH21614)
- `Series.compress()` is deprecated. Use `Series[condition]` instead (GH18262)
- The signature of *`Series.to_csv()`* has been uniformed to that of *`DataFrame.to_csv()`*: the name of the first argument is now `path_or_buf`, the order of subsequent arguments has changed, the `header` argument now defaults to `True`. (GH19715)
- *`Categorical.from_codes()`* has deprecated providing float values for the `codes` argument. (GH21767)
- *`pandas.read_table()`* is deprecated. Instead, use *`read_csv()`* passing `sep='\t'` if necessary. This deprecation has been removed in 0.25.0. (GH21948)
- *`Series.str.cat()`* has deprecated using arbitrary list-likes *within* list-likes. A list-like container may still contain many `Series`, `Index` or 1-dimensional `np.ndarray`, or alternatively, only scalar values. (GH21950)
- `FrozenNDArray.searchsorted()` has deprecated the `v` parameter in favor of `value` (GH14645)
- `DatetimeIndex.shift()` and `PeriodIndex.shift()` now accept `periods` argument instead of `n` for consistency with *`Index.shift()`* and *`Series.shift()`*. Using `n` throws a deprecation warning (GH22458, GH22912)
- The `fastpath` keyword of the different Index constructors is deprecated (GH23110).
- *`Timestamp.tz_localize()`*, *`DatetimeIndex.tz_localize()`*, and *`Series.tz_localize()`* have deprecated the `errors` argument in favor of the `nonexistent` argument (GH8917)
- The class `FrozenNDArray` has been deprecated. When unpickling, `FrozenNDArray` will be unpickled to `np.ndarray` once this class is removed (GH9031)
- The methods *`DataFrame.update()`* and `Panel.update()` have deprecated the `raise_conflict=False|True` keyword in favor of `errors='ignore'|'raise'` (GH23585)
- The methods *`Series.str.partition()`* and *`Series.str.rpartition()`* have deprecated the `pat` keyword in favor of `sep` (GH22676)
- Deprecated the `nthreads` keyword of *`pandas.read_feather()`* in favor of `use_threads` to reflect the changes in `pyarrow>=0.11.0`. (GH23053)
- *`pandas.read_excel()`* has deprecated accepting `usecols` as an integer. Please pass in a list of ints from 0 to `usecols` inclusive instead (GH23527)

- Constructing a *TimedeltaIndex* from data with datetime64-dtyped data is deprecated, will raise TypeError in a future version (GH23539)
- Constructing a *DatetimeIndex* from data with timedelta64-dtyped data is deprecated, will raise TypeError in a future version (GH23675)
- The keep_tz=False option (the default) of the keep_tz keyword of *DatetimeIndex.to_series()* is deprecated (GH17832).
- Timezone converting a tz-aware datetime.datetime or *Timestamp* with *Timestamp* and the tz argument is now deprecated. Instead, use *Timestamp.tz_convert()* (GH23579)
- pandas.api.types.is_period() is deprecated in favor of pandas.api.types.is_period_dtype (GH23917)
- pandas.api.types.is_datetimetz() is deprecated in favor of pandas.api.types.is_datetime64tz (GH23917)
- Creating a *TimedeltaIndex*, *DatetimeIndex*, or *PeriodIndex* by passing range arguments start, end, and periods is deprecated in favor of *timedelta_range()*, *date_range()*, or *period_range()* (GH23919)
- Passing a string alias like 'datetime64[ns, UTC]' as the unit parameter to *DatetimeTZDtype* is deprecated. Use DatetimeTZDtype.construct_from_string instead (GH23990).
- The skipna parameter of *infer_dtype()* will switch to True by default in a future version of pandas (GH17066, GH24050)
- In *Series.where()* with Categorical data, providing an other that is not present in the categories is deprecated. Convert the categorical to a different dtype or add the other to the categories first (GH24077).
- Series.clip_lower(), Series.clip_upper(), DataFrame.clip_lower() and DataFrame.clip_upper() are deprecated and will be removed in a future version. Use Series.clip(lower=threshold), Series.clip(upper=threshold) and the equivalent DataFrame methods (GH24203)
- Series.nonzero() is deprecated and will be removed in a future version (GH18262)
- Passing an integer to *Series.fillna()* and *DataFrame.fillna()* with timedelta64[ns] dtypes is deprecated, will raise TypeError in a future version. Use obj.fillna(pd.Timedelta(...)) instead (GH24694)
- Series.cat.categorical, Series.cat.name and Series.cat.index have been deprecated. Use the attributes on Series.cat or Series directly. (GH24751).
- Passing a dtype without a precision like np.dtype('datetime64') or timedelta64 to *Index*, *DatetimeIndex* and *TimedeltaIndex* is now deprecated. Use the nanosecond-precision dtype instead (GH24753).

Integer addition/subtraction with datetimes and timedeltas is deprecated

In the past, users could—in some cases—add or subtract integers or integer-dtype arrays from *Timestamp*, *DatetimeIndex* and *TimedeltaIndex*.

This usage is now deprecated. Instead add or subtract integer multiples of the object's freq attribute (GH21939, GH23878).

Previous behavior:

```
In [5]: ts = pd.Timestamp('1994-05-06 12:15:16', freq=pd.offsets.Hour())
In [6]: ts + 2
Out[6]: Timestamp('1994-05-06 14:15:16', freq='H')

In [7]: tdi = pd.timedelta_range('1D', periods=2)
In [8]: tdi - np.array([2, 1])
Out[8]: TimedeltaIndex(['-1 days', '1 days'], dtype='timedelta64[ns]', freq=None)

In [9]: dti = pd.date_range('2001-01-01', periods=2, freq='7D')
In [10]: dti + pd.Index([1, 2])
Out[10]: DatetimeIndex(['2001-01-08', '2001-01-22'], dtype='datetime64[ns]',␣
↪freq=None)
```

New behavior:

```
In [108]: ts = pd.Timestamp('1994-05-06 12:15:16', freq=pd.offsets.Hour())

In [109]: ts + 2 * ts.freq
Out[109]: Timestamp('1994-05-06 14:15:16', freq='H')

In [110]: tdi = pd.timedelta_range('1D', periods=2)

In [111]: tdi - np.array([2 * tdi.freq, 1 * tdi.freq])
Out[111]: TimedeltaIndex(['-1 days', '1 days'], dtype='timedelta64[ns]', freq=None)

In [112]: dti = pd.date_range('2001-01-01', periods=2, freq='7D')

In [113]: dti + pd.Index([1 * dti.freq, 2 * dti.freq])
Out[113]: DatetimeIndex(['2001-01-08', '2001-01-22'], dtype='datetime64[ns]',␣
↪freq=None)
```

Passing integer data and a timezone to DatetimeIndex

The behavior of *DatetimeIndex* when passed integer data and a timezone is changing in a future version of pandas. Previously, these were interpreted as wall times in the desired timezone. In the future, these will be interpreted as wall times in UTC, which are then converted to the desired timezone (GH24559).

The default behavior remains the same, but issues a warning:

```
In [3]: pd.DatetimeIndex([946684800000000000], tz="US/Central")
/bin/ipython:1: FutureWarning:
    Passing integer-dtype data and a timezone to DatetimeIndex. Integer values
    will be interpreted differently in a future version of pandas. Previously,
    these were viewed as datetime64[ns] values representing the wall time
    *in the specified timezone*. In the future, these will be viewed as
    datetime64[ns] values representing the wall time *in UTC*. This is similar
    to a nanosecond-precision UNIX epoch. To accept the future behavior, use

        pd.to_datetime(integer_data, utc=True).tz_convert(tz)

    To keep the previous behavior, use

        pd.to_datetime(integer_data).tz_localize(tz)

 #!/bin/python3
 Out[3]: DatetimeIndex(['2000-01-01 00:00:00-06:00'], dtype='datetime64[ns, US/
↪Central]', freq=None)
```

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As the warning message explains, opt in to the future behavior by specifying that the integer values are UTC, and then converting to the final timezone:

```
In [114]: pd.to_datetime([946684800000000000], utc=True).tz_convert('US/Central')
Out[114]: DatetimeIndex(['1999-12-31 18:00:00-06:00'], dtype='datetime64[ns, US/
↪Central]', freq=None)
```

The old behavior can be retained with by localizing directly to the final timezone:

```
In [115]: pd.to_datetime([946684800000000000]).tz_localize('US/Central')
Out[115]: DatetimeIndex(['2000-01-01 00:00:00-06:00'], dtype='datetime64[ns, US/
↪Central]', freq=None)
```

Converting timezone-aware Series and Index to NumPy arrays

The conversion from a *Series* or *Index* with timezone-aware datetime data will change to preserve timezones by default (GH23569).

NumPy doesn't have a dedicated dtype for timezone-aware datetimes. In the past, converting a *Series* or *DatetimeIndex* with timezone-aware datatimes would convert to a NumPy array by

1. converting the tz-aware data to UTC
2. dropping the timezone-info
3. returning a `numpy.ndarray` with `datetime64[ns]` dtype

Future versions of pandas will preserve the timezone information by returning an object-dtype NumPy array where each value is a *Timestamp* with the correct timezone attached

```
In [116]: ser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))

In [117]: ser
Out[117]:
0   2000-01-01 00:00:00+01:00
1   2000-01-02 00:00:00+01:00
Length: 2, dtype: datetime64[ns, CET]
```

The default behavior remains the same, but issues a warning

```
In [8]: np.asarray(ser)
/bin/ipython:1: FutureWarning: Converting timezone-aware DatetimeArray to timezone-
↪naive
      ndarray with 'datetime64[ns]' dtype. In the future, this will return an ndarray
      with 'object' dtype where each element is a 'pandas.Timestamp' with the correct
↪'tz'.

        To accept the future behavior, pass 'dtype=object'.
        To keep the old behavior, pass 'dtype="datetime64[ns]"'.
  #!/bin/python3
Out[8]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

The previous or future behavior can be obtained, without any warnings, by specifying the `dtype`

Previous behavior

```
In [118]: np.asarray(ser, dtype='datetime64[ns]')
Out[118]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

Future behavior

```
# New behavior
In [119]: np.asarray(ser, dtype=object)
Out[119]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or by using *Series.to_numpy()*

```
In [120]: ser.to_numpy()
Out[120]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)

In [121]: ser.to_numpy(dtype="datetime64[ns]")
Out[121]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

All the above applies to a *DatetimeIndex* with tz-aware values as well.

Removal of prior version deprecations/changes

- The `LongPanel` and `WidePanel` classes have been removed (GH10892)
- *Series.repeat()* has renamed the `reps` argument to `repeats` (GH14645)
- Several private functions were removed from the (non-public) module `pandas.core.common` (GH22001)
- Removal of the previously deprecated module `pandas.core.datetools` (GH14105, GH14094)
- Strings passed into *DataFrame.groupby()* that refer to both column and index levels will raise a `ValueError` (GH14432)
- *Index.repeat()* and `MultiIndex.repeat()` have renamed the `n` argument to `repeats` (GH14645)
- The `Series` constructor and `.astype` method will now raise a `ValueError` if timestamp dtypes are passed in without a unit (e.g. `np.datetime64`) for the `dtype` parameter (GH15987)
- Removal of the previously deprecated `as_indexer` keyword completely from `str.match()` (GH22356, GH6581)
- The modules `pandas.types`, `pandas.computation`, and `pandas.util.decorators` have been removed (GH16157, GH16250)
- Removed the `pandas.formats.style` shim for *pandas.io.formats.style.Styler* (GH16059)
- `pandas.pnow`, `pandas.match`, `pandas.groupby`, `pd.get_store`, `pd.Expr`, and `pd.Term` have been removed (GH15538, GH15940)

- `Categorical.searchsorted()` and *`Series.searchsorted()`* have renamed the `v` argument to `value` (GH14645)
- `pandas.parser`, `pandas.lib`, and `pandas.tslib` have been removed (GH15537)
- *`Index.searchsorted()`* have renamed the `key` argument to `value` (GH14645)
- `DataFrame.consolidate` and `Series.consolidate` have been removed (GH15501)
- Removal of the previously deprecated module `pandas.json` (GH19944)
- The module `pandas.tools` has been removed (GH15358, GH16005)
- `SparseArray.get_values()` and `SparseArray.to_dense()` have dropped the `fill` parameter (GH14686)
- `DataFrame.sortlevel` and `Series.sortlevel` have been removed (GH15099)
- `SparseSeries.to_dense()` has dropped the `sparse_only` parameter (GH14686)
- *`DataFrame.astype()`* and *`Series.astype()`* have renamed the `raise_on_error` argument to `errors` (GH14967)
- `is_sequence`, `is_any_int_dtype`, and `is_floating_dtype` have been removed from `pandas.api.types` (GH16163, GH16189)

Performance improvements

- Slicing Series and DataFrames with an monotonically increasing *`CategoricalIndex`* is now very fast and has speed comparable to slicing with an `Int64Index`. The speed increase is both when indexing by label (using .loc) and position(.iloc) (GH20395) Slicing a monotonically increasing *`CategoricalIndex`* itself (i.e. `ci[1000:2000]`) shows similar speed improvements as above (GH21659)
- Improved performance of *`CategoricalIndex.equals()`* when comparing to another *`CategoricalIndex`* (GH24023)
- Improved performance of *`Series.describe()`* in case of numeric dtpyes (GH21274)
- Improved performance of *`pandas.core.groupby.GroupBy.rank()`* when dealing with tied rankings (GH21237)
- Improved performance of *`DataFrame.set_index()`* with columns consisting of *`Period`* objects (GH21582, GH21606)
- Improved performance of *`Series.at()`* and *`Index.get_value()`* for Extension Arrays values (e.g. *`Categorical`*) (GH24204)
- Improved performance of membership checks in *`Categorical`* and *`CategoricalIndex`* (i.e. `x in cat`-style checks are much faster). `CategoricalIndex.contains()` is likewise much faster (GH21369, GH21508)
- Improved performance of *`HDFStore.groups()`* (and dependent functions like *`HDFStore.keys()`*. (i.e. `x in store` checks are much faster) (GH21372)
- Improved the performance of *`pandas.get_dummies()`* with `sparse=True` (GH21997)
- Improved performance of `IndexEngine.get_indexer_non_unique()` for sorted, non-unique indexes (GH9466)
- Improved performance of `PeriodIndex.unique()` (GH23083)
- Improved performance of *`concat()`* for `Series` objects (GH23404)

- Improved performance of *DatetimeIndex.normalize()* and *Timestamp.normalize()* for timezone naive or UTC datetimes (GH23634)
- Improved performance of *DatetimeIndex.tz_localize()* and various DatetimeIndex attributes with dateutil UTC timezone (GH23772)
- Fixed a performance regression on Windows with Python 3.7 of *read_csv()* (GH23516)
- Improved performance of *Categorical* constructor for Series objects (GH23814)
- Improved performance of *where()* for Categorical data (GH24077)
- Improved performance of iterating over a *Series*. Using *DataFrame.itertuples()* now creates iterators without internally allocating lists of all elements (GH20783)
- Improved performance of *Period* constructor, additionally benefitting PeriodArray and PeriodIndex creation (GH24084, GH24118)
- Improved performance of tz-aware DatetimeArray binary operations (GH24491)

Bug fixes

Categorical

- Bug in *Categorical.from_codes()* where NaN values in codes were silently converted to 0 (GH21767). In the future this will raise a ValueError. Also changes the behavior of .from_codes([1.1, 2.0]).
- Bug in Categorical.sort_values() where NaN values were always positioned in front regardless of na_position value. (GH22556).
- Bug when indexing with a boolean-valued Categorical. Now a boolean-valued Categorical is treated as a boolean mask (GH22665)
- Constructing a *CategoricalIndex* with empty values and boolean categories was raising a ValueError after a change to dtype coercion (GH22702).
- Bug in Categorical.take() with a user-provided fill_value not encoding the fill_value, which could result in a ValueError, incorrect results, or a segmentation fault (GH23296).
- In *Series.unstack()*, specifying a fill_value not present in the categories now raises a TypeError rather than ignoring the fill_value (GH23284)
- Bug when resampling *DataFrame.resample()* and aggregating on categorical data, the categorical dtype was getting lost. (GH23227)
- Bug in many methods of the .str-accessor, which always failed on calling the CategoricalIndex.str constructor (GH23555, GH23556)
- Bug in *Series.where()* losing the categorical dtype for categorical data (GH24077)
- Bug in Categorical.apply() where NaN values could be handled unpredictably. They now remain unchanged (GH24241)
- Bug in *Categorical* comparison methods incorrectly raising ValueError when operating against a *DataFrame* (GH24630)
- Bug in Categorical.set_categories() where setting fewer new categories with rename=True caused a segmentation fault (GH24675)

Datetimelike

- Fixed bug where two `DateOffset` objects with different `normalize` attributes could evaluate as equal (GH21404)
- Fixed bug where *`Timestamp.resolution()`* incorrectly returned 1-microsecond `timedelta` instead of 1-nanosecond *`Timedelta`* (GH21336, GH21365)
- Bug in *`to_datetime()`* that did not consistently return an *`Index`* when `box=True` was specified (GH21864)
- Bug in *`DatetimeIndex`* comparisons where string comparisons incorrectly raises `TypeError` (GH22074)
- Bug in *`DatetimeIndex`* comparisons when comparing against `timedelta64[ns]` dtyped arrays; in some cases `TypeError` was incorrectly raised, in others it incorrectly failed to raise (GH22074)
- Bug in *`DatetimeIndex`* comparisons when comparing against object-dtyped arrays (GH22074)
- Bug in *`DataFrame`* with `datetime64[ns]` dtype addition and subtraction with `Timedelta`-like objects (GH22005, GH22163)
- Bug in *`DataFrame`* with `datetime64[ns]` dtype addition and subtraction with `DateOffset` objects returning an `object` dtype instead of `datetime64[ns]` dtype (GH21610, GH22163)
- Bug in *`DataFrame`* with `datetime64[ns]` dtype comparing against `NaT` incorrectly (GH22242, GH22163)
- Bug in *`DataFrame`* with `datetime64[ns]` dtype subtracting `Timestamp`-like object incorrectly returned `datetime64[ns]` dtype instead of `timedelta64[ns]` dtype (GH8554, GH22163)
- Bug in *`DataFrame`* with `datetime64[ns]` dtype subtracting `np.datetime64` object with non-nanosecond unit failing to convert to nanoseconds (GH18874, GH22163)
- Bug in *`DataFrame`* comparisons against `Timestamp`-like objects failing to raise `TypeError` for inequality checks with mismatched types (GH8932, GH22163)
- Bug in *`DataFrame`* with mixed dtypes including `datetime64[ns]` incorrectly raising `TypeError` on equality comparisons (GH13128, GH22163)
- Bug in *`DataFrame.values`* returning a *`DatetimeIndex`* for a single-column `DataFrame` with tz-aware datetime values. Now a 2-D `numpy.ndarray` of *`Timestamp`* objects is returned (GH24024)
- Bug in *`DataFrame.eq()`* comparison against `NaT` incorrectly returning `True` or `NaN` (GH15697, GH22163)
- Bug in *`DatetimeIndex`* subtraction that incorrectly failed to raise `OverflowError` (GH22492, GH22508)
- Bug in *`DatetimeIndex`* incorrectly allowing indexing with `Timedelta` object (GH20464)
- Bug in *`DatetimeIndex`* where frequency was being set if original frequency was `None` (GH22150)
- Bug in rounding methods of *`DatetimeIndex`* (*`round()`*, *`ceil()`*, *`floor()`*) and *`Timestamp`* (*`round()`*, *`ceil()`*, *`floor()`*) could give rise to loss of precision (GH22591)
- Bug in *`to_datetime()`* with an *`Index`* argument that would drop the `name` from the result (GH21697)
- Bug in *`PeriodIndex`* where adding or subtracting a `timedelta` or `Tick` object produced incorrect results (GH22988)
- Bug in the *`Series`* repr with period-dtype data missing a space before the data (GH23601)
- Bug in *`date_range()`* when decrementing a start date to a past end date by a negative frequency (GH23270)
- Bug in *`Series.min()`* which would return `NaN` instead of `NaT` when called on a series of `NaT` (GH23282)
- Bug in *`Series.combine_first()`* not properly aligning categoricals, so that missing values in `self` where not filled by valid values from `other` (GH24147)

- Bug in *DataFrame.combine()* with datetimelike values raising a TypeError (GH23079)
- Bug in *date_range()* with frequency of Day or higher where dates sufficiently far in the future could wrap around to the past instead of raising OutOfBoundsDatetime (GH14187)
- Bug in *period_range()* ignoring the frequency of start and end when those are provided as *Period* objects (GH20535).
- Bug in *PeriodIndex* with attribute freq.n greater than 1 where adding a DateOffset object would return incorrect results (GH23215)
- Bug in *Series* that interpreted string indices as lists of characters when setting datetimelike values (GH23451)
- Bug in *DataFrame* when creating a new column from an ndarray of *Timestamp* objects with timezones creating an object-dtype column, rather than datetime with timezone (GH23932)
- Bug in *Timestamp* constructor which would drop the frequency of an input *Timestamp* (GH22311)
- Bug in *DatetimeIndex* where calling np.array(dtindex, dtype=object) would incorrectly return an array of long objects (GH23524)
- Bug in *Index* where passing a timezone-aware *DatetimeIndex* and dtype=object would incorrectly raise a ValueError (GH23524)
- Bug in *Index* where calling np.array(dtindex, dtype=object) on a timezone-naive *DatetimeIndex* would return an array of datetime objects instead of *Timestamp* objects, potentially losing nanosecond portions of the timestamps (GH23524)
- Bug in Categorical.__setitem__ not allowing setting with another Categorical when both are unordered and have the same categories, but in a different order (GH24142)
- Bug in *date_range()* where using dates with millisecond resolution or higher could return incorrect values or the wrong number of values in the index (GH24110)
- Bug in *DatetimeIndex* where constructing a *DatetimeIndex* from a *Categorical* or *CategoricalIndex* would incorrectly drop timezone information (GH18664)
- Bug in *DatetimeIndex* and *TimedeltaIndex* where indexing with Ellipsis would incorrectly lose the index's freq attribute (GH21282)
- Clarified error message produced when passing an incorrect freq argument to *DatetimeIndex* with NaT as the first entry in the passed data (GH11587)
- Bug in *to_datetime()* where box and utc arguments were ignored when passing a *DataFrame* or dict of unit mappings (GH23760)
- Bug in *Series.dt* where the cache would not update properly after an in-place operation (GH24408)
- Bug in *PeriodIndex* where comparisons against an array-like object with length 1 failed to raise ValueError (GH23078)
- Bug in DatetimeIndex.astype(), PeriodIndex.astype() and TimedeltaIndex.astype() ignoring the sign of the dtype for unsigned integer dtypes (GH24405).
- Fixed bug in *Series.max()* with datetime64[ns]-dtype failing to return NaT when nulls are present and skipna=False is passed (GH24265)
- Bug in *to_datetime()* where arrays of datetime objects containing both timezone-aware and timezone-naive datetimes would fail to raise ValueError (GH24569)
- Bug in *to_datetime()* with invalid datetime format doesn't coerce input to NaT even if errors='coerce' (GH24763)

Timedelta

- Bug in *DataFrame* with `timedelta64[ns]` dtype division by `Timedelta`-like scalar incorrectly returning `timedelta64[ns]` dtype instead of `float64` dtype (GH20088, GH22163)
- Bug in adding a *Index* with object dtype to a *Series* with `timedelta64[ns]` dtype incorrectly raising (GH22390)
- Bug in multiplying a *Series* with numeric dtype against a `timedelta` object (GH22390)
- Bug in *Series* with numeric dtype when adding or subtracting an array or `Series` with `timedelta64` dtype (GH22390)
- Bug in *Index* with numeric dtype when multiplying or dividing an array with dtype `timedelta64` (GH22390)
- Bug in *TimedeltaIndex* incorrectly allowing indexing with `Timestamp` object (GH20464)
- Fixed bug where subtracting *Timedelta* from an object-dtyped array would raise `TypeError` (GH21980)
- Fixed bug in adding a *DataFrame* with all-*timedelta64[ns]* dtypes to a *DataFrame* with all-integer dtypes returning incorrect results instead of raising `TypeError` (GH22696)
- Bug in *TimedeltaIndex* where adding a timezone-aware datetime scalar incorrectly returned a timezone-naive *DatetimeIndex* (GH23215)
- Bug in *TimedeltaIndex* where adding `np.timedelta64('NaT')` incorrectly returned an all-`NaT` *DatetimeIndex* instead of an all-`NaT` *TimedeltaIndex* (GH23215)
- Bug in *Timedelta* and *to_timedelta()* have inconsistencies in supported unit string (GH21762)
- Bug in *TimedeltaIndex* division where dividing by another *TimedeltaIndex* raised `TypeError` instead of returning a *Float64Index* (GH23829, GH22631)
- Bug in *TimedeltaIndex* comparison operations where comparing against non-`Timedelta`-like objects would raise `TypeError` instead of returning all-`False` for `__eq__` and all-`True` for `__ne__` (GH24056)
- Bug in *Timedelta* comparisons when comparing with a `Tick` object incorrectly raising `TypeError` (GH24710)

Timezones

- Bug in *Index.shift()* where an `AssertionError` would raise when shifting across DST (GH8616)
- Bug in *Timestamp* constructor where passing an invalid timezone offset designator (`Z`) would not raise a `ValueError` (GH8910)
- Bug in *Timestamp.replace()* where replacing at a DST boundary would retain an incorrect offset (GH7825)
- Bug in *Series.replace()* with `datetime64[ns, tz]` data when replacing `NaT` (GH11792)
- Bug in *Timestamp* when passing different string date formats with a timezone offset would produce different timezone offsets (GH12064)
- Bug when comparing a tz-naive *Timestamp* to a tz-aware *DatetimeIndex* which would coerce the *DatetimeIndex* to tz-naive (GH12601)
- Bug in *Series.truncate()* with a tz-aware *DatetimeIndex* which would cause a core dump (GH9243)
- Bug in *Series* constructor which would coerce tz-aware and tz-naive *Timestamp* to tz-aware (GH13051)
- Bug in *Index* with `datetime64[ns, tz]` dtype that did not localize integer data correctly (GH20964)

- Bug in *DatetimeIndex* where constructing with an integer and tz would not localize correctly (GH12619)
- Fixed bug where *DataFrame.describe()* and *Series.describe()* on tz-aware datetimes did not show `first` and `last` result (GH21328)
- Bug in *DatetimeIndex* comparisons failing to raise `TypeError` when comparing timezone-aware `DatetimeIndex` against `np.datetime64` (GH22074)
- Bug in `DataFrame` assignment with a timezone-aware scalar (GH19843)
- Bug in *DataFrame.asof()* that raised a `TypeError` when attempting to compare tz-naive and tz-aware timestamps (GH21194)
- Bug when constructing a *DatetimeIndex* with *Timestamp* constructed with the `replace` method across DST (GH18785)
- Bug when setting a new value with *DataFrame.loc()* with a *DatetimeIndex* with a DST transition (GH18308, GH20724)
- Bug in *Index.unique()* that did not re-localize tz-aware dates correctly (GH21737)
- Bug when indexing a *Series* with a DST transition (GH21846)
- Bug in *DataFrame.resample()* and *Series.resample()* where an `AmbiguousTimeError` or `NonExistentTimeError` would raise if a timezone aware timeseries ended on a DST transition (GH19375, GH10117)
- Bug in *DataFrame.drop()* and *Series.drop()* when specifying a tz-aware Timestamp key to drop from a *DatetimeIndex* with a DST transition (GH21761)
- Bug in *DatetimeIndex* constructor where `NaT` and `dateutil.tz.tzlocal` would raise an `OutOfBoundsDatetime` error (GH23807)
- Bug in *DatetimeIndex.tz_localize()* and *Timestamp.tz_localize()* with `dateutil.tz.tzlocal` near a DST transition that would return an incorrectly localized datetime (GH23807)
- Bug in *Timestamp* constructor where a `dateutil.tz.tzutc` timezone passed with a `datetime.datetime` argument would be converted to a `pytz.UTC` timezone (GH23807)
- Bug in *to_datetime()* where `utc=True` was not respected when specifying a `unit` and `errors='ignore'` (GH23758)
- Bug in *to_datetime()* where `utc=True` was not respected when passing a *Timestamp* (GH24415)
- Bug in *DataFrame.any()* returns wrong value when `axis=1` and the data is of datetimelike type (GH23070)
- Bug in *DatetimeIndex.to_period()* where a timezone aware index was converted to UTC first before creating *PeriodIndex* (GH22905)
- Bug in *DataFrame.tz_localize()*, *DataFrame.tz_convert()*, *Series.tz_localize()*, and *Series.tz_convert()* where `copy=False` would mutate the original argument inplace (GH6326)
- Bug in *DataFrame.max()* and *DataFrame.min()* with `axis=1` where a *Series* with `NaN` would be returned when all columns contained the same timezone (GH10390)

Offsets

- Bug in `FY5253` where date offsets could incorrectly raise an `AssertionError` in arithmetic operations (GH14774)
- Bug in `DateOffset` where keyword arguments `week` and `milliseconds` were accepted and ignored. Passing these will now raise `ValueError` (GH19398)
- Bug in adding `DateOffset` with *DataFrame* or *PeriodIndex* incorrectly raising `TypeError` (GH23215)
- Bug in comparing `DateOffset` objects with non-DateOffset objects, particularly strings, raising `ValueError` instead of returning `False` for equality checks and `True` for not-equal checks (GH23524)

Numeric

- Bug in *Series* `__rmatmul__` doesn't support matrix vector multiplication (GH21530)
- Bug in *factorize()* fails with read-only array (GH12813)
- Fixed bug in *unique()* handled signed zeros inconsistently: for some inputs 0.0 and -0.0 were treated as equal and for some inputs as different. Now they are treated as equal for all inputs (GH21866)
- Bug in *DataFrame.agg()*, *DataFrame.transform()* and *DataFrame.apply()* where, when supplied with a list of functions and `axis=1` (e.g. `df.apply(['sum', 'mean'], axis=1)`), a `TypeError` was wrongly raised. For all three methods such calculation are now done correctly. (GH16679).
- Bug in *Series* comparison against datetime-like scalars and arrays (GH22074)
- Bug in *DataFrame* multiplication between boolean dtype and integer returning `object` dtype instead of integer dtype (GH22047, GH22163)
- Bug in *DataFrame.apply()* where, when supplied with a string argument and additional positional or keyword arguments (e.g. `df.apply('sum', min_count=1)`), a `TypeError` was wrongly raised (GH22376)
- Bug in *DataFrame.astype()* to extension dtype may raise `AttributeError` (GH22578)
- Bug in *DataFrame* with `timedelta64[ns]` dtype arithmetic operations with `ndarray` with integer dtype incorrectly treating the narray as `timedelta64[ns]` dtype (GH23114)
- Bug in *Series.rpow()* with object dtype `NaN` for `1 ** NA` instead of `1` (GH22922).
- *Series.agg()* can now handle numpy NaN-aware methods like `numpy.nansum()` (GH19629)
- Bug in *Series.rank()* and *DataFrame.rank()* when `pct=True` and more than 2^{24} rows are present resulted in percentages greater than 1.0 (GH18271)
- Calls such as *DataFrame.round()* with a non-unique *CategoricalIndex()* now return expected data. Previously, data would be improperly duplicated (GH21809).
- Added `log10`, `floor` and `ceil` to the list of supported functions in *DataFrame.eval()* (GH24139, GH24353)
- Logical operations `&, |, ^` between *Series* and *Index* will no longer raise `ValueError` (GH22092)
- Checking PEP 3141 numbers in *is_scalar()* function returns `True` (GH22903)
- Reduction methods like *Series.sum()* now accept the default value of `keepdims=False` when called from a NumPy ufunc, rather than raising a `TypeError`. Full support for `keepdims` has not been implemented (GH24356).

Conversion

- Bug in *DataFrame.combine_first()* in which column types were unexpectedly converted to float (GH20699)
- Bug in *DataFrame.clip()* in which column types are not preserved and casted to float (GH24162)
- Bug in *DataFrame.clip()* when order of columns of dataframes doesn't match, result observed is wrong in numeric values (GH20911)
- Bug in *DataFrame.astype()* where converting to an extension dtype when duplicate column names are present causes a `RecursionError` (GH24704)

Strings

- Bug in `Index.str.partition()` was not nan-safe (GH23558).
- Bug in `Index.str.split()` was not nan-safe (GH23677).
- Bug *Series.str.contains()* not respecting the `na` argument for a `Categorical` dtype `Series` (GH22158)
- Bug in `Index.str.cat()` when the result contained only `NaN` (GH24044)

Interval

- Bug in the *IntervalIndex* constructor where the `closed` parameter did not always override the inferred `closed` (GH19370)
- Bug in the `IntervalIndex` repr where a trailing comma was missing after the list of intervals (GH20611)
- Bug in *Interval* where scalar arithmetic operations did not retain the `closed` value (GH22313)
- Bug in *IntervalIndex* where indexing with datetime-like values raised a `KeyError` (GH20636)
- Bug in `IntervalTree` where data containing `NaN` triggered a warning and resulted in incorrect indexing queries with *IntervalIndex* (GH23352)

Indexing

- Bug in *DataFrame.ne()* fails if columns contain column name "dtype" (GH22383)
- The traceback from a `KeyError` when asking `.loc` for a single missing label is now shorter and more clear (GH21557)
- *PeriodIndex* now emits a `KeyError` when a malformed string is looked up, which is consistent with the behavior of *DatetimeIndex* (GH22803)
- When `.ix` is asked for a missing integer label in a *MultiIndex* with a first level of integer type, it now raises a `KeyError`, consistently with the case of a flat *Int64Index*, rather than falling back to positional indexing (GH21593)
- Bug in *Index.reindex()* when reindexing a tz-naive and tz-aware *DatetimeIndex* (GH8306)
- Bug in *Series.reindex()* when reindexing an empty series with a `datetime64[ns, tz]` dtype (GH20869)
- Bug in *DataFrame* when setting values with `.loc` and a timezone aware *DatetimeIndex* (GH11365)

- `DataFrame.__getitem__` now accepts dictionaries and dictionary keys as list-likes of labels, consistently with `Series.__getitem__` (GH21294)
- Fixed `DataFrame[np.nan]` when columns are non-unique (GH21428)
- Bug when indexing *`DatetimeIndex`* with nanosecond resolution dates and timezones (GH11679)
- Bug where indexing with a Numpy array containing negative values would mutate the indexer (GH21867)
- Bug where mixed indexes wouldn't allow integers for `.at` (GH19860)
- `Float64Index.get_loc` now raises `KeyError` when boolean key passed. (GH19087)
- Bug in *`DataFrame.loc()`* when indexing with an *`IntervalIndex`* (GH19977)
- *`Index`* no longer mangles `None`, `NaN` and `NaT`, i.e. they are treated as three different keys. However, for numeric Index all three are still coerced to a `NaN` (GH22332)
- Bug in `scalar in Index` if scalar is a float while the `Index` is of integer dtype (GH22085)
- Bug in *`MultiIndex.set_levels()`* when levels value is not subscriptable (GH23273)
- Bug where setting a timedelta column by `Index` causes it to be casted to double, and therefore lose precision (GH23511)
- Bug in *`Index.union()`* and *`Index.intersection()`* where name of the `Index` of the result was not computed correctly for certain cases (GH9943, GH9862)
- Bug in *`Index`* slicing with boolean *`Index`* may raise `TypeError` (GH22533)
- Bug in `PeriodArray.__setitem__` when accepting slice and list-like value (GH23978)
- Bug in *`DatetimeIndex`*, *`TimedeltaIndex`* where indexing with `Ellipsis` would lose their `freq` attribute (GH21282)
- Bug in `iat` where using it to assign an incompatible value would create a new column (GH23236)

Missing

- Bug in *`DataFrame.fillna()`* where a `ValueError` would raise when one column contained a `datetime64[ns, tz]` dtype (GH15522)
- Bug in *`Series.hasnans()`* that could be incorrectly cached and return incorrect answers if null elements are introduced after an initial call (GH19700)
- *`Series.isin()`* now treats all NaN-floats as equal also for `np.object`-dtype. This behavior is consistent with the behavior for float64 (GH22119)
- *`unique()`* no longer mangles NaN-floats and the `NaT`-object for `np.object`-dtype, i.e. `NaT` is no longer coerced to a NaN-value and is treated as a different entity. (GH22295)
- *`DataFrame`* and *`Series`* now properly handle numpy masked arrays with hardened masks. Previously, constructing a DataFrame or Series from a masked array with a hard mask would create a pandas object containing the underlying value, rather than the expected NaN. (GH24574)
- Bug in *`DataFrame`* constructor where `dtype` argument was not honored when handling numpy masked record arrays. (GH24874)

MultiIndex

- Bug in *io.formats.style.Styler.applymap()* where `subset=` with *MultiIndex* slice would reduce to *Series* (GH19861)
- Removed compatibility for *MultiIndex* pickles prior to version 0.8.0; compatibility with *MultiIndex* pickles from version 0.13 forward is maintained (GH21654)
- *MultiIndex.get_loc_level()* (and as a consequence, `.loc` on a `Series` or `DataFrame` with a *MultiIndex* index) will now raise a `KeyError`, rather than returning an empty `slice`, if asked a label which is present in the `levels` but is unused (GH22221)
- *MultiIndex* has gained the *MultiIndex.from_frame()*, it allows constructing a *MultiIndex* object from a *DataFrame* (GH22420)
- Fix `TypeError` in Python 3 when creating *MultiIndex* in which some levels have mixed types, e.g. when some labels are tuples (GH15457)

IO

- Bug in *read_csv()* in which a column specified with `CategoricalDtype` of boolean categories was not being correctly coerced from string values to booleans (GH20498)
- Bug in *read_csv()* in which unicode column names were not being properly recognized with Python 2.x (GH13253)
- Bug in *DataFrame.to_sql()* when writing timezone aware data (`datetime64[ns, tz]` dtype) would raise a `TypeError` (GH9086)
- Bug in *DataFrame.to_sql()* where a naive *DatetimeIndex* would be written as `TIMESTAMP WITH TIMEZONE` type in supported databases, e.g. PostgreSQL (GH23510)
- Bug in *read_excel()* when `parse_cols` is specified with an empty dataset (GH9208)
- *read_html()* no longer ignores all-whitespace `<tr>` within `<thead>` when considering the `skiprows` and `header` arguments. Previously, users had to decrease their `header` and `skiprows` values on such tables to work around the issue. (GH21641)
- *read_excel()* will correctly show the deprecation warning for previously deprecated `sheetname` (GH17994)
- *read_csv()* and *read_table()* will throw `UnicodeError` and not coredump on badly encoded strings (GH22748)
- *read_csv()* will correctly parse timezone-aware datetimes (GH22256)
- Bug in *read_csv()* in which memory management was prematurely optimized for the C engine when the data was being read in chunks (GH23509)
- Bug in *read_csv()* in unnamed columns were being improperly identified when extracting a multi-index (GH23687)
- *read_sas()* will parse numbers in sas7bdat-files that have width less than 8 bytes correctly. (GH21616)
- *read_sas()* will correctly parse sas7bdat files with many columns (GH22628)
- *read_sas()* will correctly parse sas7bdat files with data page types having also bit 7 set (so page type is 128 + 256 = 384) (GH16615)
- Bug in *read_sas()* in which an incorrect error was raised on an invalid file format. (GH24548)

- Bug in `detect_client_encoding()` where potential `IOError` goes unhandled when importing in a mod_wsgi process due to restricted access to stdout. (GH21552)
- Bug in *DataFrame.to_html()* with `index=False` misses truncation indicators (...) on truncated DataFrame (GH15019, GH22783)
- Bug in *DataFrame.to_html()* with `index=False` when both columns and row index are `MultiIndex` (GH22579)
- Bug in *DataFrame.to_html()* with `index_names=False` displaying index name (GH22747)
- Bug in *DataFrame.to_html()* with `header=False` not displaying row index names (GH23788)
- Bug in *DataFrame.to_html()* with `sparsify=False` that caused it to raise `TypeError` (GH22887)
- Bug in *DataFrame.to_string()* that broke column alignment when `index=False` and width of first column's values is greater than the width of first column's header (GH16839, GH13032)
- Bug in *DataFrame.to_string()* that caused representations of *DataFrame* to not take up the whole window (GH22984)
- Bug in *DataFrame.to_csv()* where a single level MultiIndex incorrectly wrote a tuple. Now just the value of the index is written (GH19589).
- `HDFStore` will raise `ValueError` when the `format` kwarg is passed to the constructor (GH13291)
- Bug in *HDFStore.append()* when appending a *DataFrame* with an empty string column and `min_itemsize` < 8 (GH12242)
- Bug in *read_csv()* in which memory leaks occurred in the C engine when parsing `NaN` values due to insufficient cleanup on completion or error (GH21353)
- Bug in *read_csv()* in which incorrect error messages were being raised when `skipfooter` was passed in along with `nrows`, `iterator`, or `chunksize` (GH23711)
- Bug in *read_csv()* in which *MultiIndex* index names were being improperly handled in the cases when they were not provided (GH23484)
- Bug in *read_csv()* in which unnecessary warnings were being raised when the dialect's values conflicted with the default arguments (GH23761)
- Bug in *read_html()* in which the error message was not displaying the valid flavors when an invalid one was provided (GH23549)
- Bug in *read_excel()* in which extraneous header names were extracted, even though none were specified (GH11733)
- Bug in *read_excel()* in which column names were not being properly converted to string sometimes in Python 2.x (GH23874)
- Bug in *read_excel()* in which `index_col=None` was not being respected and parsing index columns anyway (GH18792, GH20480)
- Bug in *read_excel()* in which `usecols` was not being validated for proper column names when passed in as a string (GH20480)
- Bug in *DataFrame.to_dict()* when the resulting dict contains non-Python scalars in the case of numeric data (GH23753)
- *DataFrame.to_string()*, *DataFrame.to_html()*, *DataFrame.to_latex()* will correctly format output when a string is passed as the `float_format` argument (GH21625, GH22270)
- Bug in *read_csv()* that caused it to raise `OverflowError` when trying to use 'inf' as `na_value` with integer index column (GH17128)

- Bug in *read_csv()* that caused the C engine on Python 3.6+ on Windows to improperly read CSV filenames with accented or special characters (GH15086)
- Bug in *read_fwf()* in which the compression type of a file was not being properly inferred (GH22199)
- Bug in `pandas.io.json.json_normalize()` that caused it to raise `TypeError` when two consecutive elements of `record_path` are dicts (GH22706)
- Bug in *DataFrame.to_stata()*, `pandas.io.stata.StataWriter` and `pandas.io.stata.StataWriter117` where a exception would leave a partially written and invalid dta file (GH23573)
- Bug in *DataFrame.to_stata()* and `pandas.io.stata.StataWriter117` that produced invalid files when using strLs with non-ASCII characters (GH23573)
- Bug in `HDFStore` that caused it to raise `ValueError` when reading a Dataframe in Python 3 from fixed format written in Python 2 (GH24510)
- Bug in *DataFrame.to_string()* and more generally in the floating `repr` formatter. Zeros were not trimmed if `inf` was present in a columns while it was the case with NA values. Zeros are now trimmed as in the presence of NA (GH24861).
- Bug in the `repr` when truncating the number of columns and having a wide last column (GH24849).

Plotting

- Bug in *DataFrame.plot.scatter()* and *DataFrame.plot.hexbin()* caused x-axis label and ticklabels to disappear when colorbar was on in IPython inline backend (GH10611, GH10678, and GH20455)
- Bug in plotting a Series with datetimes using `matplotlib.axes.Axes.scatter()` (GH22039)
- Bug in *DataFrame.plot.bar()* caused bars to use multiple colors instead of a single one (GH20585)
- Bug in validating color parameter caused extra color to be appended to the given color array. This happened to multiple plotting functions using matplotlib. (GH20726)

GroupBy/resample/rolling

- Bug in `pandas.core.window.Rolling.min()` and `pandas.core.window.Rolling.max()` with `closed='left'`, a datetime-like index and only one entry in the series leading to segfault (GH24718)
- Bug in *pandas.core.groupby.GroupBy.first()* and *pandas.core.groupby.GroupBy.last()* with `as_index=False` leading to the loss of timezone information (GH15884)
- Bug in `DateFrame.resample()` when downsampling across a DST boundary (GH8531)
- Bug in date anchoring for `DateFrame.resample()` with offset `Day` when n > 1 (GH24127)
- Bug where `ValueError` is wrongly raised when calling `count()` method of a `SeriesGroupBy` when the grouping variable only contains NaNs and numpy version < 1.13 (GH21956).
- Multiple bugs in `pandas.core.window.Rolling.min()` with `closed='left'` and a datetime-like index leading to incorrect results and also segfault. (GH21704)
- Bug in *pandas.core.resample.Resampler.apply()* when passing positional arguments to applied func (GH14615).
- Bug in *Series.resample()* when passing `numpy.timedelta64` to `loffset` kwarg (GH7687).
- Bug in *pandas.core.resample.Resampler.asfreq()* when frequency of `TimedeltaIndex` is a subperiod of a new frequency (GH13022).

- Bug in `pandas.core.groupby.SeriesGroupBy.mean()` when values were integral but could not fit inside of int64, overflowing instead. (GH22487)
- `pandas.core.groupby.RollingGroupby.agg()` and `pandas.core.groupby.ExpandingGroupby.agg()` now support multiple aggregation functions as parameters (GH15072)
- Bug in *DataFrame.resample()* and *Series.resample()* when resampling by a weekly offset (`'W'`) across a DST transition (GH9119, GH21459)
- Bug in *DataFrame.expanding()* in which the `axis` argument was not being respected during aggregations (GH23372)
- Bug in `pandas.core.groupby.GroupBy.transform()` which caused missing values when the input function can accept a *DataFrame* but renames it (GH23455).
- Bug in *pandas.core.groupby.GroupBy.nth()* where column order was not always preserved (GH20760)
- Bug in *pandas.core.groupby.GroupBy.rank()* with `method='dense'` and `pct=True` when a group has only one member would raise a `ZeroDivisionError` (GH23666).
- Calling *pandas.core.groupby.GroupBy.rank()* with empty groups and `pct=True` was raising a `ZeroDivisionError` (GH22519)
- Bug in *DataFrame.resample()* when resampling `NaT` in `TimeDeltaIndex` (GH13223).
- Bug in *DataFrame.groupby()* did not respect the `observed` argument when selecting a column and instead always used `observed=False` (GH23970)
- Bug in `pandas.core.groupby.SeriesGroupBy.pct_change()` or *pandas.core.groupby.DataFrameGroupBy.pct_change()* would previously work across groups when calculating the percent change, where it now correctly works per group (GH21200, GH21235).
- Bug preventing hash table creation with very large number (2^32) of rows (GH22805)
- Bug in groupby when grouping on categorical causes `ValueError` and incorrect grouping if `observed=True` and `nan` is present in categorical column (GH24740, GH21151).

Reshaping

- Bug in *pandas.concat()* when joining resampled DataFrames with timezone aware index (GH13783)
- Bug in *pandas.concat()* when joining only `Series` the `names` argument of `concat` is no longer ignored (GH23490)
- Bug in *Series.combine_first()* with `datetime64[ns, tz]` dtype which would return tz-naive result (GH21469)
- Bug in *Series.where()* and *DataFrame.where()* with `datetime64[ns, tz]` dtype (GH21546)
- Bug in *DataFrame.where()* with an empty DataFrame and empty `cond` having non-bool dtype (GH21947)
- Bug in *Series.mask()* and *DataFrame.mask()* with `list` conditionals (GH21891)
- Bug in *DataFrame.replace()* raises RecursionError when converting OutOfBounds `datetime64[ns, tz]` (GH20380)
- *pandas.core.groupby.GroupBy.rank()* now raises a `ValueError` when an invalid value is passed for argument `na_option` (GH22124)
- Bug in *get_dummies()* with Unicode attributes in Python 2 (GH22084)
- Bug in *DataFrame.replace()* raises `RecursionError` when replacing empty lists (GH22083)

- Bug in *Series.replace()* and *DataFrame.replace()* when dict is used as the `to_replace` value and one key in the dict is another key's value, the results were inconsistent between using integer key and using string key (GH20656)
- Bug in *DataFrame.drop_duplicates()* for empty `DataFrame` which incorrectly raises an error (GH20516)
- Bug in *pandas.wide_to_long()* when a string is passed to the stubnames argument and a column name is a substring of that stubname (GH22468)
- Bug in *merge()* when merging `datetime64[ns, tz]` data that contained a DST transition (GH18885)
- Bug in *merge_asof()* when merging on float values within defined tolerance (GH22981)
- Bug in *pandas.concat()* when concatenating a multicolumn DataFrame with tz-aware data against a DataFrame with a different number of columns (GH22796)
- Bug in *merge_asof()* where confusing error message raised when attempting to merge with missing values (GH23189)
- Bug in *DataFrame.nsmallest()* and *DataFrame.nlargest()* for dataframes that have a *MultiIndex* for columns (GH23033).
- Bug in *pandas.melt()* when passing column names that are not present in `DataFrame` (GH23575)
- Bug in *DataFrame.append()* with a *Series* with a dateutil timezone would raise a `TypeError` (GH23682)
- Bug in *Series* construction when passing no data and `dtype=str` (GH22477)
- Bug in *cut()* with `bins` as an overlapping `IntervalIndex` where multiple bins were returned per item instead of raising a `ValueError` (GH23980)
- Bug in *pandas.concat()* when joining `Series` datetimetz with `Series` category would lose timezone (GH23816)
- Bug in *DataFrame.join()* when joining on partial MultiIndex would drop names (GH20452).
- *DataFrame.nlargest()* and *DataFrame.nsmallest()* now returns the correct n values when keep != 'all' also when tied on the first columns (GH22752)
- Constructing a DataFrame with an index argument that wasn't already an instance of `Index` was broken (GH22227).
- Bug in *DataFrame* prevented list subclasses to be used to construction (GH21226)
- Bug in *DataFrame.unstack()* and *DataFrame.pivot_table()* returning a misleading error message when the resulting DataFrame has more elements than int32 can handle. Now, the error message is improved, pointing towards the actual problem (GH20601)
- Bug in *DataFrame.unstack()* where a `ValueError` was raised when unstacking timezone aware values (GH18338)
- Bug in *DataFrame.stack()* where timezone aware values were converted to timezone naive values (GH19420)
- Bug in *merge_asof()* where a `TypeError` was raised when `by_col` were timezone aware values (GH21184)
- Bug showing an incorrect shape when throwing error during `DataFrame` construction. (GH20742)

Sparse

- Updating a boolean, datetime, or timedelta column to be Sparse now works (GH22367)
- Bug in `Series.to_sparse()` with Series already holding sparse data not constructing properly (GH22389)
- Providing a `sparse_index` to the SparseArray constructor no longer defaults the na-value to `np.nan` for all dtypes. The correct na_value for `data.dtype` is now used.
- Bug in `SparseArray.nbytes` under-reporting its memory usage by not including the size of its sparse index.
- Improved performance of *`Series.shift()`* for non-NA `fill_value`, as values are no longer converted to a dense array.
- Bug in `DataFrame.groupby` not including `fill_value` in the groups for non-NA `fill_value` when grouping by a sparse column (GH5078)
- Bug in unary inversion operator (~) on a `SparseSeries` with boolean values. The performance of this has also been improved (GH22835)
- Bug in `SparseArary.unique()` not returning the unique values (GH19595)
- Bug in `SparseArray.nonzero()` and `SparseDataFrame.dropna()` returning shifted/incorrect results (GH21172)
- Bug in *`DataFrame.apply()`* where dtypes would lose sparseness (GH23744)
- Bug in *`concat()`* when concatenating a list of *`Series`* with all-sparse values changing the `fill_value` and converting to a dense Series (GH24371)

Style

- *`background_gradient()`* now takes a `text_color_threshold` parameter to automatically lighten the text color based on the luminance of the background color. This improves readability with dark background colors without the need to limit the background colormap range. (GH21258)
- *`background_gradient()`* now also supports tablewise application (in addition to rowwise and columnwise) with `axis=None` (GH15204)
- *`bar()`* now also supports tablewise application (in addition to rowwise and columnwise) with `axis=None` and setting clipping range with `vmin` and `vmax` (GH21548 and GH21526). `NaN` values are also handled properly.

Build changes

- Building pandas for development now requires `cython >= 0.28.2` (GH21688)
- Testing pandas now requires `hypothesis>=3.58`. You can find the Hypothesis docs here, and a pandas-specific introduction *in the contributing guide*. (GH22280)
- Building pandas on macOS now targets minimum macOS 10.9 if run on macOS 10.9 or above (GH23424)

Other

- Bug where C variables were declared with external linkage causing import errors if certain other C libraries were imported before pandas. (GH24113)

Contributors

A total of 337 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- James Myatt +
- James Winegar +

- Jan Rudolph
- Jared Groves +
- Jason Kiley +
- Javad Noorbakhsh +
- Jay Offerdahl +
- Jeff Reback
- Jeongmin Yu +
- Jeremy Schendel
- Jerod Estapa +
- Jesper Dramsch +
- Jim Jeon +
- Joe Jevnik
- Joel Nothman
- Joel Ostblom +
- Jordi Contestí
- Jorge López Fueyo +
- Joris Van den Bossche
- Jose Quinones +
- Jose Rivera-Rubio +
- Josh
- Jun +
- Justin Zheng +
- Kaiqi Dong +
- Kalyan Gokhale
- Kang Yoosam +
- Karl Dunkle Werner +
- Karmanya Aggarwal +
- Kevin Markham +
- Kevin Sheppard
- Kimi Li +
- Koustav Samaddar +
- Krishna +
- Kristian Holsheimer +
- Ksenia Gueletina +
- Kyle Prestel +
- LJ +

- LeakedMemory +
- Li Jin +
- Licht Takeuchi
- Luca Donini +
- Luciano Viola +
- Mak Sze Chun +
- Marc Garcia
- Marius Potgieter +
- Mark Sikora +
- Markus Meier +
- Marlene Silva Marchena +
- Martin Babka +
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- Mateusz Woś +
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- Matt Boggess +
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- Matthew Roeschke
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- Michael Odintsov
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- Mickaël Schoentgen +
- Miguel Sánchez de León Peque +
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- Mitch Negus
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- Parfait G +
- Patrick Park +
- Paul
- Paul Ganssle
- Paul Reidy
- Paul van Mulbregt +
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- Prabakaran Kumaresshan +
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- Pyry Kovanen
- Rajib Mitra +
- Redonnet Louis +
- Rhys Parry +
- Rick +
- Robin
- Roei.r +
- RomainSa +
- Roman Imankulov +
- Roman Yurchak +
- Ruijing Li +
- Ryan +
- Ryan Nazareth +
- Rüdiger Busche +
- SEUNG HOON, SHIN +
- Sandrine Pataut +
- Sangwoong Yoon
- Santosh Kumar +
- Saurav Chakravorty +
- Scott McAllister +

- Sean Chan +
- Shadi Akiki +
- Shengpu Tang +
- Shirish Kadam +
- Simon Hawkins +
- Simon Riddell +
- Simone Basso
- Sinhrks
- Soyoun(Rose) Kim +
- Srinivas Reddy Thatiparthy ( ) +
- Stefaan Lippens +
- Stefano Cianciulli
- Stefano Miccoli +
- Stephen Childs
- Stephen Pascoe
- Steve Baker +
- Steve Cook +
- Steve Dower +
- Stéphan Taljaard +
- Sumin Byeon +
- Sören +
- Tamas Nagy +
- Tanya Jain +
- Tarbo Fukazawa
- Thein Oo +
- Thiago Cordeiro da Fonseca +
- Thierry Moisan
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- Thomas Lentali +
- Tim D. Smith +
- Tim Swast
- Tom Augspurger
- Tomasz Kluczkowski +
- Tony Tao +
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- Troels Nielsen +

- Tuhin Mahmud +
- Tyler Reddy +
- Uddeshya Singh
- Uwe L. Korn +
- Vadym Barda +
- Varad Gunjal +
- Victor Maryama +
- Victor Villas
- Vincent La
- Vitória Helena +
- Vu Le
- Vyom Jain +
- Weiwen Gu +
- Wenhuan
- Wes Turner
- Wil Tan +
- William Ayd
- Yeojin Kim +
- Yitzhak Andrade +
- Yuecheng Wu +
- Yuliya Dovzhenko +
- Yury Bayda +
- Zac Hatfield-Dodds +
- aberres +
- aeltanawy +
- ailchau +
- alimcmaster1
- alphaCTzo7G +
- amphy +
- araraonline +
- azure-pipelines[bot] +
- benarthur91 +
- bk521234 +
- cgangwar11 +
- chris-b1
- cxl923cc +

- dahlbaek +
- dannyhyunkim +
- darke-spirits +
- david-liu-brattle-1
- davidmvalente +
- deflatSOCO
- doosik_bae +
- dylanchase +
- eduardo naufel schettino +
- euri10 +
- evangelineliu +
- fengyqf +
- fjdiod
- fl4p +
- fleimgruber +
- gfyoung
- h-vetinari
- harisbal +
- henriqueribeiro +
- himanshu awasthi
- hongshaoyang +
- igorfassen +
- jalazbe +
- jbrockmendel
- jh-wu +
- justinchan23 +
- louispotok
- marcosrullan +
- miker985
- nicolab100 +
- nprad
- nsuresh +
- ottiP
- pajachiet +
- raguiar2 +
- ratijas +

- realead +
- robbuckley +
- saurav2608 +
- sideeye +
- ssikdar1
- svenharris +
- syutbai +
- testvinder +
- thatneat
- tmnhat2001
- tomascassidy +
- tomneep
- topper-123
- vkk800 +
- winlu +
- ym-pett +
- yrhooke +
- ywpark1 +
- zertrin
- zhezherun +

5.6 Version 0.23

5.6.1 What's new in 0.23.4 (August 3, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What's new in v0.23.4

- *Fixed regressions*
- *Bug fixes*
- *Contributors*

Fixed regressions

- Python 3.7 with Windows gave all missing values for rolling variance calculations (GH21813)

Bug fixes

Groupby/resample/rolling

- Bug where calling `DataFrameGroupBy.agg()` with a list of functions including `ohlc` as the non-initial element would raise a `ValueError` (GH21716)
- Bug in `roll_quantile` caused a memory leak when calling `.rolling(...).quantile(q)` with `q` in (0,1) (GH21965)

Missing

- Bug in *`Series.clip()`* and *`DataFrame.clip()`* cannot accept list-like threshold containing `NaN` (GH19992)

Contributors

A total of 6 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Jeff Reback
- MeeseeksMachine +
- Tom Augspurger
- chris-b1
- h-vetinari
- meeseeksdev[bot]

5.6.2 What's new in 0.23.3 (July 7, 2018)

This release fixes a build issue with the sdist for Python 3.7 (GH21785) There are no other changes.

Contributors

A total of 2 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Tom Augspurger
- meeseeksdev[bot] +

5.6.3 What's new in 0.23.2 (July 5, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

Note: pandas 0.23.2 is first pandas release that's compatible with Python 3.7 (GH20552)

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What's new in v0.23.2

- *Logical reductions over entire DataFrame*
- *Fixed regressions*
- *Build changes*
- *Bug fixes*
- *Contributors*

Logical reductions over entire DataFrame

`DataFrame.all()` and `DataFrame.any()` now accept `axis=None` to reduce over all axes to a scalar (GH19976)

```
In [1]: df = pd.DataFrame({"A": [1, 2], "B": [True, False]})

In [2]: df.all(axis=None)
Out[2]: False
```

This also provides compatibility with NumPy 1.15, which now dispatches to `DataFrame.all`. With NumPy 1.15 and pandas 0.23.1 or earlier, `numpy.all()` will no longer reduce over every axis:

```
>>> # NumPy 1.15, pandas 0.23.1
>>> np.any(pd.DataFrame({"A": [False], "B": [False]}))
A    False
B    False
dtype: bool
```

With pandas 0.23.2, that will correctly return False, as it did with NumPy < 1.15.

```
In [3]: np.any(pd.DataFrame({"A": [False], "B": [False]}))
Out[3]: False
```

Fixed regressions

- Fixed regression in `to_csv()` when handling file-like object incorrectly (GH21471)
- Re-allowed duplicate level names of a `MultiIndex`. Accessing a level that has a duplicate name by name still raises an error (GH19029).
- Bug in both *`DataFrame.first_valid_index()`* and *`Series.first_valid_index()`* raised for a row index having duplicate values (GH21441)
- Fixed printing of DataFrames with hierarchical columns with long names (GH21180)
- Fixed regression in *`reindex()`* and *`groupby()`* with a MultiIndex or multiple keys that contains categorical datetime-like values (GH21390).
- Fixed regression in unary negative operations with object dtype (GH21380)
- Bug in *`Timestamp.ceil()`* and *`Timestamp.floor()`* when timestamp is a multiple of the rounding frequency (GH21262)
- Fixed regression in `to_clipboard()` that defaulted to copying dataframes with space delimited instead of tab delimited (GH21104)

Build changes

- The source and binary distributions no longer include test data files, resulting in smaller download sizes. Tests relying on these data files will be skipped when using `pandas.test()`. (GH19320)

Bug fixes

Conversion

- Bug in constructing *`Index`* with an iterator or generator (GH21470)
- Bug in *`Series.nlargest()`* for signed and unsigned integer dtypes when the minimum value is present (GH21426)

Indexing

- Bug in *`Index.get_indexer_non_unique()`* with categorical key (GH21448)
- Bug in comparison operations for *`MultiIndex`* where error was raised on equality / inequality comparison involving a MultiIndex with `nlevels == 1` (GH21149)
- Bug in *`DataFrame.drop()`* behaviour is not consistent for unique and non-unique indexes (GH21494)
- Bug in *`DataFrame.duplicated()`* with a large number of columns causing a 'maximum recursion depth exceeded' (GH21524).

I/O

- Bug in *`read_csv()`* that caused it to incorrectly raise an error when `nrows=0`, `low_memory=True`, and `index_col` was not `None` (GH21141)
- Bug in *`json_normalize()`* when formatting the `record_prefix` with integer columns (GH21536)

Categorical

- Bug in rendering *`Series`* with `Categorical` dtype in rare conditions under Python 2.7 (GH21002)

Timezones

- Bug in *Timestamp* and *DatetimeIndex* where passing a *Timestamp* localized after a DST transition would return a datetime before the DST transition (GH20854)
- Bug in comparing *DataFrame* with tz-aware *DatetimeIndex* columns with a DST transition that raised a KeyError (GH19970)
- Bug in DatetimeIndex.shift() where an AssertionError would raise when shifting across DST (GH8616)
- Bug in *Timestamp* constructor where passing an invalid timezone offset designator (Z) would not raise a ValueError (GH8910)
- Bug in *Timestamp.replace()* where replacing at a DST boundary would retain an incorrect offset (GH7825)
- Bug in DatetimeIndex.reindex() when reindexing a tz-naive and tz-aware *DatetimeIndex* (GH8306)
- Bug in DatetimeIndex.resample() when downsampling across a DST boundary (GH8531)

Timedelta

- Bug in *Timedelta* where non-zero timedeltas shorter than 1 microsecond were considered False (GH21484)

Contributors

A total of 17 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- David Krych
- Jacopo Rota +
- Jeff Reback
- Jeremy Schendel
- Joris Van den Bossche
- Kalyan Gokhale
- Matthew Roeschke
- Michael Odintsov +
- Ming Li
- Pietro Battiston
- Tom Augspurger
- Uddeshya Singh
- Vu Le +
- alimcmaster1 +
- david-liu-brattle-1 +
- gfyoung
- jbrockmendel

5.6.4 What's new in 0.23.1 (June 12, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What's new in v0.23.1

- *Fixed regressions*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

Fixed regressions

Comparing Series with datetime.date

We've reverted a 0.23.0 change to comparing a *Series* holding datetimes and a `datetime.date` object (GH21152). In pandas 0.22 and earlier, comparing a Series holding datetimes and `datetime.date` objects would coerce the `datetime.date` to a datetime before comparing. This was inconsistent with Python, NumPy, and *DatetimeIndex*, which never consider a datetime and `datetime.date` equal.

In 0.23.0, we unified operations between DatetimeIndex and Series, and in the process changed comparisons between a Series of datetimes and `datetime.date` without warning.

We've temporarily restored the 0.22.0 behavior, so datetimes and dates may again compare equal, but restore the 0.23.0 behavior in a future release.

To summarize, here's the behavior in 0.22.0, 0.23.0, 0.23.1:

```
# 0.22.0... Silently coerce the datetime.date
>>> import datetime
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
0     True
1    False
dtype: bool

# 0.23.0... Do not coerce the datetime.date
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
0    False
1    False
dtype: bool

# 0.23.1... Coerce the datetime.date with a warning
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
/bin/python:1: FutureWarning: Comparing Series of datetimes with 'datetime.date'.
↪Currently, the
'datetime.date' is coerced to a datetime. In the future pandas will
not coerce, and the values not compare equal to the 'datetime.date'.
To retain the current behavior, convert the 'datetime.date' to a
```

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```
datetime with 'pd.Timestamp'.
  #!/bin/python3
0     True
1    False
dtype: bool
```

In addition, ordering comparisons will raise a `TypeError` in the future.

Other fixes

- Reverted the ability of *to_sql()* to perform multivalue inserts as this caused regression in certain cases (GH21103). In the future this will be made configurable.
- Fixed regression in the *DatetimeIndex.date* and *DatetimeIndex.time* attributes in case of timezone-aware data: *DatetimeIndex.time* returned a tz-aware time instead of tz-naive (GH21267) and *DatetimeIndex.date* returned incorrect date when the input date has a non-UTC timezone (GH21230).
- Fixed regression in `pandas.io.json.json_normalize()` when called with `None` values in nested levels in JSON, and to not drop keys with value as `None` (GH21158, GH21356).
- Bug in *to_csv()* causes encoding error when compression and encoding are specified (GH21241, GH21118)
- Bug preventing pandas from being importable with -OO optimization (GH21071)
- Bug in `Categorical.fillna()` incorrectly raising a `TypeError` when `value` the individual categories are iterable and `value` is an iterable (GH21097, GH19788)
- Fixed regression in constructors coercing NA values like `None` to strings when passing `dtype=str` (GH21083)
- Regression in *pivot_table()* where an ordered `Categorical` with missing values for the pivot's `index` would give a mis-aligned result (GH21133)
- Fixed regression in merging on boolean index/columns (GH21119).

Performance improvements

- Improved performance of `CategoricalIndex.is_monotonic_increasing()`, `CategoricalIndex.is_monotonic_decreasing()` and `CategoricalIndex.is_monotonic()` (GH21025)
- Improved performance of `CategoricalIndex.is_unique()` (GH21107)

Bug fixes

Groupby/resample/rolling

- Bug in *DataFrame.agg()* where applying multiple aggregation functions to a *DataFrame* with duplicated column names would cause a stack overflow (GH21063)
- Bug in *pandas.core.groupby.GroupBy.ffill()* and *pandas.core.groupby.GroupBy.bfill()* where the fill within a grouping would not always be applied as intended due to the implementations' use of a non-stable sort (GH21207)
- Bug in *pandas.core.groupby.GroupBy.rank()* where results did not scale to 100% when specifying `method='dense'` and `pct=True`
- Bug in *pandas.DataFrame.rolling()* and *pandas.Series.rolling()* which incorrectly accepted a 0 window size rather than raising (GH21286)

Data-type specific

- Bug in *Series.str.replace()* where the method throws TypeError on Python 3.5.2 (GH21078)
- Bug in *Timedelta* where passing a float with a unit would prematurely round the float precision (GH14156)
- Bug in *pandas.testing.assert_index_equal()* which raised AssertionError incorrectly, when comparing two *CategoricalIndex* objects with param check_categorical=False (GH19776)

Sparse

- Bug in SparseArray.shape which previously only returned the shape SparseArray.sp_values (GH21126)

Indexing

- Bug in *Series.reset_index()* where appropriate error was not raised with an invalid level name (GH20925)
- Bug in *interval_range()* when start/periods or end/periods are specified with float start or end (GH21161)
- Bug in MultiIndex.set_names() where error raised for a MultiIndex with nlevels == 1 (GH21149)
- Bug in *IntervalIndex* constructors where creating an IntervalIndex from categorical data was not fully supported (GH21243, GH21253)
- Bug in MultiIndex.sort_index() which was not guaranteed to sort correctly with level=1; this was also causing data misalignment in particular *DataFrame.stack()* operations (GH20994, GH20945, GH21052)

Plotting

- New keywords (sharex, sharey) to turn on/off sharing of x/y-axis by subplots generated with pandas.DataFrame().groupby().boxplot() (GH20968)

I/O

- Bug in IO methods specifying compression='zip' which produced uncompressed zip archives (GH17778, GH21144)
- Bug in *DataFrame.to_stata()* which prevented exporting DataFrames to buffers and most file-like objects (GH21041)
- Bug in *read_stata()* and StataReader which did not correctly decode utf-8 strings on Python 3 from Stata 14 files (dta version 118) (GH21244)
- Bug in IO JSON *read_json()* reading empty JSON schema with orient='table' back to *DataFrame* caused an error (GH21287)

Reshaping

- Bug in *concat()* where error was raised in concatenating *Series* with numpy scalar and tuple names (GH21015)
- Bug in *concat()* warning message providing the wrong guidance for future behavior (GH21101)

Other

- Tab completion on *Index* in IPython no longer outputs deprecation warnings (GH21125)
- Bug preventing pandas being used on Windows without C++ redistributable installed (GH21106)

Contributors

A total of 30 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Adam J. Stewart
- Adam Kim +
- Aly Sivji
- Chalmer Lowe +
- Damini Satya +
- Dr. Irv
- Gabe Fernando +
- Giftlin Rajaiah
- Jeff Reback
- Jeremy Schendel +
- Joris Van den Bossche
- Kalyan Gokhale +
- Kevin Sheppard
- Matthew Roeschke
- Max Kanter +
- Ming Li
- Pyry Kovanen +
- Stefano Cianciulli
- Tom Augspurger
- Uddeshya Singh +
- Wenhuan
- William Ayd
- chris-b1
- gfyoung
- h-vetinari
- nprad +
- ssikdar1 +
- tmnhat2001
- topper-123
- zertrin +

5.6.5 What's new in 0.23.0 (May 15, 2018)

This is a major release from 0.22.0 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- *Round-trippable JSON format with 'table' orient*.
- *Instantiation from dicts respects order for Python 3.6+*.
- *Dependent column arguments for assign*.
- *Merging / sorting on a combination of columns and index levels*.
- *Extending pandas with custom types*.
- *Excluding unobserved categories from groupby*.
- *Changes to make output shape of DataFrame.apply consistent*.

Check the *API Changes* and *deprecations* before updating.

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What's new in v0.23.0

- *New features*
  - *JSON read/write round-trippable with* `orient='table'`
  - *Method* `.assign()` *accepts dependent arguments*
  - *Merging on a combination of columns and index levels*
  - *Sorting by a combination of columns and index levels*
  - *Extending pandas with custom types (experimental)*
  - *New* `observed` *keyword for excluding unobserved categories in* `GroupBy`
  - *Rolling/Expanding.apply() accepts* `raw=False` *to pass a* `Series` *to the function*
  - `DataFrame.interpolate` *has gained the* `limit_area` *kwarg*
  - *Function* `get_dummies` *now supports* `dtype` *argument*
  - *Timedelta mod method*
  - *Method* `.rank()` *handles* `inf` *values when* `NaN` *are present*
  - `Series.str.cat` *has gained the* `join` *kwarg*
  - `DataFrame.astype` *performs column-wise conversion to* `Categorical`
  - *Other enhancements*
- *Backwards incompatible API changes*
  - *Dependencies have increased minimum versions*
  - *Instantiation from dicts preserves dict insertion order for Python 3.6+*

- *Deprecate Panel*
- *pandas.core.common removals*
- *Changes to make output of `DataFrame.apply` consistent*
- *Concatenation will no longer sort*
- *Build changes*
- *Index division by zero fills correctly*
- *Extraction of matching patterns from strings*
- *Default value for the `ordered` parameter of `CategoricalDtype`*
- *Better pretty-printing of DataFrames in a terminal*
- *Datetimelike API changes*
- *Other API changes*

- *Deprecations*
- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Documentation changes*
- *Bug fixes*
  - *Categorical*
  - *Datetimelike*
  - *Timedelta*
  - *Timezones*
  - *Offsets*
  - *Numeric*
  - *Strings*
  - *Indexing*
  - *MultiIndex*
  - *IO*
  - *Plotting*
  - *GroupBy/resample/rolling*
  - *Sparse*
  - *Reshaping*
  - *Other*
- *Contributors*

New features

JSON read/write round-trippable with `orient='table'`

A `DataFrame` can now be written to and subsequently read back via JSON while preserving metadata through usage of the `orient='table'` argument (see GH18912 and GH9146). Previously, none of the available `orient` values guaranteed the preservation of dtypes and index names, amongst other metadata.

```
In [1]: df = pd.DataFrame({'foo': [1, 2, 3, 4],
   ...:                    'bar': ['a', 'b', 'c', 'd'],
   ...:                    'baz': pd.date_range('2018-01-01', freq='d', periods=4),
   ...:                    'qux': pd.Categorical(['a', 'b', 'c', 'c'])},
   ...:                   index=pd.Index(range(4), name='idx'))
   ...:

In [2]: df
Out[2]:
     foo bar        baz qux
idx
0      1   a 2018-01-01   a
1      2   b 2018-01-02   b
2      3   c 2018-01-03   c
3      4   d 2018-01-04   c

[4 rows x 4 columns]

In [3]: df.dtypes
Out[3]:
foo             int64
bar            object
baz    datetime64[ns]
qux          category
Length: 4, dtype: object

In [4]: df.to_json('test.json', orient='table')

In [5]: new_df = pd.read_json('test.json', orient='table')

In [6]: new_df
Out[6]:
     foo bar        baz qux
idx
0      1   a 2018-01-01   a
1      2   b 2018-01-02   b
2      3   c 2018-01-03   c
3      4   d 2018-01-04   c

[4 rows x 4 columns]

In [7]: new_df.dtypes
Out[7]:
foo             int64
bar            object
baz    datetime64[ns]
qux          category
Length: 4, dtype: object
```

Please note that the string `index` is not supported with the round trip format, as it is used by default in `write_json`

to indicate a missing index name.

```
In [8]: df.index.name = 'index'

In [9]: df.to_json('test.json', orient='table')

In [10]: new_df = pd.read_json('test.json', orient='table')

In [11]: new_df
Out[11]:
   foo bar        baz qux
0    1   a 2018-01-01   a
1    2   b 2018-01-02   b
2    3   c 2018-01-03   c
3    4   d 2018-01-04   c

[4 rows x 4 columns]

In [12]: new_df.dtypes
Out[12]:
foo              int64
bar             object
baz     datetime64[ns]
qux           category
Length: 4, dtype: object
```

Method `.assign()` accepts dependent arguments

The *`DataFrame.assign()`* now accepts dependent keyword arguments for python version later than 3.6 (see also PEP 468). Later keyword arguments may now refer to earlier ones if the argument is a callable. See the *documentation here* (GH14207)

```
In [13]: df = pd.DataFrame({'A': [1, 2, 3]})

In [14]: df
Out[14]:
   A
0  1
1  2
2  3

[3 rows x 1 columns]

In [15]: df.assign(B=df.A, C=lambda x: x['A'] + x['B'])
Out[15]:
   A  B  C
0  1  1  2
1  2  2  4
2  3  3  6

[3 rows x 3 columns]
```

Warning: This may subtly change the behavior of your code when you're using `.assign()` to update an existing column. Previously, callables referring to other variables being updated would get the "old" values

Previous behavior:

```
In [2]: df = pd.DataFrame({"A": [1, 2, 3]})

In [3]: df.assign(A=lambda df: df.A + 1, C=lambda df: df.A * -1)
Out[3]:
   A  C
0  2 -1
1  3 -2
2  4 -3
```

New behavior:

```
In [16]: df.assign(A=df.A + 1, C=lambda df: df.A * -1)
Out[16]:
   A  C
0  2 -2
1  3 -3
2  4 -4

[3 rows x 2 columns]
```

Merging on a combination of columns and index levels

Strings passed to *DataFrame.merge()* as the `on`, `left_on`, and `right_on` parameters may now refer to either column names or index level names. This enables merging `DataFrame` instances on a combination of index levels and columns without resetting indexes. See the *Merge on columns and levels* documentation section. (GH14355)

```
In [17]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [18]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                      'B': ['B0', 'B1', 'B2', 'B3'],
   ....:                      'key2': ['K0', 'K1', 'K0', 'K1']},
   ....:                     index=left_index)
   ....:

In [19]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [20]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                       'D': ['D0', 'D1', 'D2', 'D3'],
   ....:                       'key2': ['K0', 'K0', 'K0', 'K1']},
   ....:                      index=right_index)
   ....:

In [21]: left.merge(right, on=['key1', 'key2'])
Out[21]:
       A   B key2   C   D
key1
K0    A0  B0   K0  C0  D0
K1    A2  B2   K0  C1  D1
K2    A3  B3   K1  C3  D3

[3 rows x 5 columns]
```

Sorting by a combination of columns and index levels

Strings passed to *DataFrame.sort_values()* as the `by` parameter may now refer to either column names or index level names. This enables sorting `DataFrame` instances by a combination of index levels and columns without resetting indexes. See the *Sorting by Indexes and Values* documentation section. (GH14353)

```
# Build MultiIndex
In [22]: idx = pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('a', 2),
   ....:                                  ('b', 2), ('b', 1), ('b', 1)])
   ....:

In [23]: idx.names = ['first', 'second']

# Build DataFrame
In [24]: df_multi = pd.DataFrame({'A': np.arange(6, 0, -1)},
   ....:                         index=idx)
   ....:

In [25]: df_multi
Out[25]:
              A
first second
a     1       6
      2       5
      2       4
b     2       3
      1       2
      1       1

[6 rows x 1 columns]

# Sort by 'second' (index) and 'A' (column)
In [26]: df_multi.sort_values(by=['second', 'A'])
Out[26]:
              A
first second
b     1       1
      1       2
a     1       6
b     2       3
a     2       4
      2       5

[6 rows x 1 columns]
```

Extending pandas with custom types (experimental)

pandas now supports storing array-like objects that aren't necessarily 1-D NumPy arrays as columns in a DataFrame or values in a Series. This allows third-party libraries to implement extensions to NumPy's types, similar to how pandas implemented categoricals, datetimes with timezones, periods, and intervals.

As a demonstration, we'll use cyberpandas, which provides an `IPArray` type for storing ip addresses.

```
In [1]: from cyberpandas import IPArray

In [2]: values = IPArray([
```

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```
   ...:     0,
   ...:     3232235777,
   ...:     42540766452641154071740215577757643572
   ...: ])
   ...:
   ...:
```

`IPArray` isn't a normal 1-D NumPy array, but because it's a pandas *`ExtensionArray`*, it can be stored properly inside pandas' containers.

```
In [3]: ser = pd.Series(values)

In [4]: ser
Out[4]:
0                         0.0.0.0
1                     192.168.1.1
2    2001:db8:85a3::8a2e:370:7334
dtype: ip
```

Notice that the dtype is `ip`. The missing value semantics of the underlying array are respected:

```
In [5]: ser.isna()
Out[5]:
0     True
1    False
2    False
dtype: bool
```

For more, see the *extension types* documentation. If you build an extension array, publicize it on our ecosystem page.

New `observed` keyword for excluding unobserved categories in `GroupBy`

Grouping by a categorical includes the unobserved categories in the output. When grouping by multiple categorical columns, this means you get the cartesian product of all the categories, including combinations where there are no observations, which can result in a large number of groups. We have added a keyword `observed` to control this behavior, it defaults to `observed=False` for backward-compatibility. (GH14942, GH8138, GH15217, GH17594, GH8669, GH20583, GH20902)

```
In [27]: cat1 = pd.Categorical(["a", "a", "b", "b"],
   ....:                       categories=["a", "b", "z"], ordered=True)
   ....:

In [28]: cat2 = pd.Categorical(["c", "d", "c", "d"],
   ....:                       categories=["c", "d", "y"], ordered=True)
   ....:

In [29]: df = pd.DataFrame({"A": cat1, "B": cat2, "values": [1, 2, 3, 4]})

In [30]: df['C'] = ['foo', 'bar'] * 2

In [31]: df
Out[31]:
   A  B  values    C
0  a  c       1  foo
1  a  d       2  bar
```

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```
2  b  c       3  foo
3  b  d       4  bar

[4 rows x 4 columns]
```

To show all values, the previous behavior:

```
In [32]: df.groupby(['A', 'B', 'C'], observed=False).count()
Out[32]:
         values
A B C
a c bar       0
    foo       1
  d bar       1
    foo       0
  y bar       0
...           ...
z c foo       0
  d bar       0
    foo       0
  y bar       0
    foo       0

[18 rows x 1 columns]
```

To show only observed values:

```
In [33]: df.groupby(['A', 'B', 'C'], observed=True).count()
Out[33]:
         values
A B C
a c foo       1
  d bar       1
b c foo       1
  d bar       1

[4 rows x 1 columns]
```

For pivoting operations, this behavior is *already* controlled by the `dropna` keyword:

```
In [34]: cat1 = pd.Categorical(["a", "a", "b", "b"],
   ....:                       categories=["a", "b", "z"], ordered=True)
   ....:

In [35]: cat2 = pd.Categorical(["c", "d", "c", "d"],
   ....:                       categories=["c", "d", "y"], ordered=True)
   ....:

In [36]: df = pd.DataFrame({"A": cat1, "B": cat2, "values": [1, 2, 3, 4]})

In [37]: df
Out[37]:
   A  B  values
0  a  c       1
1  a  d       2
2  b  c       3
3  b  d       4
```

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```
[4 rows x 3 columns]
```

```
In [38]: pd.pivot_table(df, values='values', index=['A', 'B'],
   ....:                  dropna=True)
   ....:
Out[38]:
     values
A B
a c       1
  d       2
b c       3
  d       4

[4 rows x 1 columns]

In [39]: pd.pivot_table(df, values='values', index=['A', 'B'],
   ....:                  dropna=False)
   ....:
Out[39]:
     values
A B
a c     1.0
  d     2.0
  y     NaN
b c     3.0
  d     4.0
  y     NaN
z c     NaN
  d     NaN
  y     NaN

[9 rows x 1 columns]
```

Rolling/Expanding.apply() accepts `raw=False` to pass a `Series` to the function

`Series.rolling().apply()`, `DataFrame.rolling().apply()`, `Series.expanding().apply()`, and `DataFrame.expanding().apply()` have gained a `raw=None` parameter. This is similar to `DataFame.apply()`. This parameter, if `True` allows one to send a `np.ndarray` to the applied function. If `False` a `Series` will be passed. The default is `None`, which preserves backward compatibility, so this will default to `True`, sending an `np.ndarray`. In a future version the default will be changed to `False`, sending a `Series`. (GH5071, GH20584)

```
In [40]: s = pd.Series(np.arange(5), np.arange(5) + 1)

In [41]: s
Out[41]:
1    0
2    1
3    2
4    3
5    4
Length: 5, dtype: int64
```

Pass a `Series`:

```
In [42]: s.rolling(2, min_periods=1).apply(lambda x: x.iloc[-1], raw=False)
Out[42]:
1    0.0
2    1.0
3    2.0
4    3.0
5    4.0
Length: 5, dtype: float64
```

Mimic the original behavior of passing a ndarray:

```
In [43]: s.rolling(2, min_periods=1).apply(lambda x: x[-1], raw=True)
Out[43]:
1    0.0
2    1.0
3    2.0
4    3.0
5    4.0
Length: 5, dtype: float64
```

`DataFrame.interpolate` has gained the `limit_area` kwarg

`DataFrame.interpolate()` has gained a `limit_area` parameter to allow further control of which `NaN` s are replaced. Use `limit_area='inside'` to fill only NaNs surrounded by valid values or use `limit_area='outside'` to fill only `NaN` s outside the existing valid values while preserving those inside. (GH16284) See the *full documentation here*.

```
In [44]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan,
   ....:                  np.nan, 13, np.nan, np.nan])
   ....:

In [45]: ser
Out[45]:
0     NaN
1     NaN
2     5.0
3     NaN
4     NaN
5     NaN
6    13.0
7     NaN
8     NaN
Length: 9, dtype: float64
```

Fill one consecutive inside value in both directions

```
In [46]: ser.interpolate(limit_direction='both', limit_area='inside', limit=1)
Out[46]:
0     NaN
1     NaN
2     5.0
3     7.0
4     NaN
5    11.0
6    13.0
```

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```
7     NaN
8     NaN
Length: 9, dtype: float64
```

Fill all consecutive outside values backward

```
In [47]: ser.interpolate(limit_direction='backward', limit_area='outside')
Out[47]:
0     5.0
1     5.0
2     5.0
3     NaN
4     NaN
5     NaN
6    13.0
7     NaN
8     NaN
Length: 9, dtype: float64
```

Fill all consecutive outside values in both directions

```
In [48]: ser.interpolate(limit_direction='both', limit_area='outside')
Out[48]:
0     5.0
1     5.0
2     5.0
3     NaN
4     NaN
5     NaN
6    13.0
7    13.0
8    13.0
Length: 9, dtype: float64
```

Function `get_dummies` now supports `dtype` argument

The *get_dummies()* now accepts a `dtype` argument, which specifies a dtype for the new columns. The default remains uint8. (GH18330)

```
In [49]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 4], 'c': [5, 6]})

In [50]: pd.get_dummies(df, columns=['c']).dtypes
Out[50]:
a      int64
b      int64
c_5    uint8
c_6    uint8
Length: 4, dtype: object

In [51]: pd.get_dummies(df, columns=['c'], dtype=bool).dtypes
Out[51]:
a      int64
b      int64
c_5     bool
```

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```
c_6     bool
Length: 4, dtype: object
```

Timedelta mod method

`mod` (%) and `divmod` operations are now defined on `Timedelta` objects when operating with either timedelta-like or with numeric arguments. See the *documentation here*. (GH19365)

```
In [52]: td = pd.Timedelta(hours=37)

In [53]: td % pd.Timedelta(minutes=45)
Out[53]: Timedelta('0 days 00:15:00')
```

Method `.rank()` handles `inf` values when `NaN` are present

In previous versions, `.rank()` would assign `inf` elements `NaN` as their ranks. Now ranks are calculated properly. (GH6945)

```
In [54]: s = pd.Series([-np.inf, 0, 1, np.nan, np.inf])

In [55]: s
Out[55]:
0   -inf
1    0.0
2    1.0
3    NaN
4    inf
Length: 5, dtype: float64
```

Previous behavior:

```
In [11]: s.rank()
Out[11]:
0    1.0
1    2.0
2    3.0
3    NaN
4    NaN
dtype: float64
```

Current behavior:

```
In [56]: s.rank()
Out[56]:
0    1.0
1    2.0
2    3.0
3    NaN
4    4.0
Length: 5, dtype: float64
```

Furthermore, previously if you rank `inf` or `-inf` values together with `NaN` values, the calculation won't distinguish `NaN` from infinity when using 'top' or 'bottom' argument.

```
In [57]: s = pd.Series([np.nan, np.nan, -np.inf, -np.inf])

In [58]: s
Out[58]:
0    NaN
1    NaN
2   -inf
3   -inf
Length: 4, dtype: float64
```

Previous behavior:

```
In [15]: s.rank(na_option='top')
Out[15]:
0    2.5
1    2.5
2    2.5
3    2.5
dtype: float64
```

Current behavior:

```
In [59]: s.rank(na_option='top')
Out[59]:
0    1.5
1    1.5
2    3.5
3    3.5
Length: 4, dtype: float64
```

These bugs were squashed:

- Bug in *DataFrame.rank()* and *Series.rank()* when `method='dense'` and `pct=True` in which percentile ranks were not being used with the number of distinct observations (GH15630)
- Bug in *Series.rank()* and *DataFrame.rank()* when `ascending='False'` failed to return correct ranks for infinity if `NaN` were present (GH19538)
- Bug in `DataFrameGroupBy.rank()` where ranks were incorrect when both infinity and `NaN` were present (GH20561)

`Series.str.cat` has gained the `join` kwarg

Previously, *Series.str.cat()* did not – in contrast to most of `pandas` – align *Series* on their index before concatenation (see GH18657). The method has now gained a keyword `join` to control the manner of alignment, see examples below and *here*.

In v.0.23 `join` will default to None (meaning no alignment), but this default will change to `'left'` in a future version of pandas.

```
In [60]: s = pd.Series(['a', 'b', 'c', 'd'])

In [61]: t = pd.Series(['b', 'd', 'e', 'c'], index=[1, 3, 4, 2])

In [62]: s.str.cat(t)
Out[62]:
0    NaN
```

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```
1     bb
2     cc
3     dd
Length: 4, dtype: object

In [63]: s.str.cat(t, join='left', na_rep='-')
Out[63]:
0    a-
1    bb
2    cc
3    dd
Length: 4, dtype: object
```

Furthermore, *Series.str.cat()* now works for `CategoricalIndex` as well (previously raised a `ValueError`; see GH20842).

`DataFrame.astype` performs column-wise conversion to `Categorical`

DataFrame.astype() can now perform column-wise conversion to `Categorical` by supplying the string `'category'` or a `CategoricalDtype`. Previously, attempting this would raise a `NotImplementedError`. See the *Object creation* section of the documentation for more details and examples. (GH12860, GH18099)

Supplying the string `'category'` performs column-wise conversion, with only labels appearing in a given column set as categories:

```
In [64]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')})

In [65]: df = df.astype('category')

In [66]: df['A'].dtype
Out[66]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=False)

In [67]: df['B'].dtype
Out[67]: CategoricalDtype(categories=['b', 'c', 'd'], ordered=False)
```

Supplying a `CategoricalDtype` will make the categories in each column consistent with the supplied dtype:

```
In [68]: from pandas.api.types import CategoricalDtype

In [69]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')})

In [70]: cdt = CategoricalDtype(categories=list('abcd'), ordered=True)

In [71]: df = df.astype(cdt)

In [72]: df['A'].dtype
Out[72]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)

In [73]: df['B'].dtype
Out[73]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)
```

Other enhancements

- Unary + now permitted for `Series` and `DataFrame` as numeric operator (GH16073)
- Better support for *`to_excel()`* output with the `xlsxwriter` engine. (GH16149)
- *`pandas.tseries.frequencies.to_offset()`* now accepts leading '+' signs e.g. '+1h'. (GH18171)
- `MultiIndex.unique()` now supports the `level=` argument, to get unique values from a specific index level (GH17896)
- *`pandas.io.formats.style.Styler`* now has method `hide_index()` to determine whether the index will be rendered in output (GH14194)
- *`pandas.io.formats.style.Styler`* now has method `hide_columns()` to determine whether columns will be hidden in output (GH14194)
- Improved wording of `ValueError` raised in *`to_datetime()`* when `unit=` is passed with a non-convertible value (GH14350)
- *`Series.fillna()`* now accepts a Series or a dict as a `value` for a categorical dtype (GH17033)
- *`pandas.read_clipboard()`* updated to use qtpy, falling back to PyQt5 and then PyQt4, adding compatibility with Python3 and multiple python-qt bindings (GH17722)
- Improved wording of `ValueError` raised in *`read_csv()`* when the `usecols` argument cannot match all columns. (GH17301)
- *`DataFrame.corrwith()`* now silently drops non-numeric columns when passed a Series. Before, an exception was raised (GH18570).
- *`IntervalIndex`* now supports time zone aware `Interval` objects (GH18537, GH18538)
- *`Series()`* / *`DataFrame()`* tab completion also returns identifiers in the first level of a *`MultiIndex()`*. (GH16326)
- *`read_excel()`* has gained the `nrows` parameter (GH16645)
- *`DataFrame.append()`* can now in more cases preserve the type of the calling dataframe's columns (e.g. if both are `CategoricalIndex`) (GH18359)
- *`DataFrame.to_json()`* and *`Series.to_json()`* now accept an `index` argument which allows the user to exclude the index from the JSON output (GH17394)
- `IntervalIndex.to_tuples()` has gained the `na_tuple` parameter to control whether NA is returned as a tuple of NA, or NA itself (GH18756)
- `Categorical.rename_categories`, `CategoricalIndex.rename_categories` and *`Series.cat.rename_categories`* can now take a callable as their argument (GH18862)
- *`Interval`* and *`IntervalIndex`* have gained a `length` attribute (GH18789)
- `Resampler` objects now have a functioning *`pipe`* method. Previously, calls to `pipe` were diverted to the `mean` method (GH17905).
- *`is_scalar()`* now returns `True` for `DateOffset` objects (GH18943).
- *`DataFrame.pivot()`* now accepts a list for the `values=` kwarg (GH17160).
- Added *`pandas.api.extensions.register_dataframe_accessor()`*, *`pandas.api.extensions.register_series_accessor()`*, and *`pandas.api.extensions.register_index_accessor()`*, accessor for libraries downstream of pandas to register custom accessors like `.cat` on pandas objects. See *Registering Custom Accessors* for more (GH14781).

- `IntervalIndex.astype` now supports conversions between subtypes when passed an `IntervalDtype` (GH19197)
- *IntervalIndex* and its associated constructor methods (`from_arrays`, `from_breaks`, `from_tuples`) have gained a `dtype` parameter (GH19262)
- Added *pandas.core.groupby.SeriesGroupBy.is_monotonic_increasing()* and *pandas.core.groupby.SeriesGroupBy.is_monotonic_decreasing()* (GH17015)
- For subclassed `DataFrames`, *DataFrame.apply()* will now preserve the `Series` subclass (if defined) when passing the data to the applied function (GH19822)
- *DataFrame.from_dict()* now accepts a `columns` argument that can be used to specify the column names when `orient='index'` is used (GH18529)
- Added option `display.html.use_mathjax` so MathJax can be disabled when rendering tables in `Jupyter` notebooks (GH19856, GH19824)
- *DataFrame.replace()* now supports the `method` parameter, which can be used to specify the replacement method when `to_replace` is a scalar, list or tuple and `value` is `None` (GH19632)
- *Timestamp.month_name()*, *DatetimeIndex.month_name()*, and *Series.dt.month_name()* are now available (GH12805)
- *Timestamp.day_name()* and *DatetimeIndex.day_name()* are now available to return day names with a specified locale (GH12806)
- *DataFrame.to_sql()* now performs a multi-value insert if the underlying connection supports itk rather than inserting row by row. `SQLAlchemy` dialects supporting multi-value inserts include: `mysql`, `postgresql`, `sqlite` and any dialect with `supports_multivalues_insert`. (GH14315, GH8953)
- *read_html()* now accepts a `displayed_only` keyword argument to controls whether or not hidden elements are parsed (`True` by default) (GH20027)
- *read_html()* now reads all `<tbody>` elements in a `<table>`, not just the first. (GH20690)
- `quantile()` and `quantile()` now accept the `interpolation` keyword, `linear` by default (GH20497)
- zip compression is supported via `compression=zip` in *DataFrame.to_pickle()*, *Series.to_pickle()*, *DataFrame.to_csv()*, *Series.to_csv()*, *DataFrame.to_json()*, *Series.to_json()*. (GH17778)
- *WeekOfMonth* constructor now supports `n=0` (GH20517).
- *DataFrame* and *Series* now support matrix multiplication (`@`) operator (GH10259) for Python>=3.5
- Updated *DataFrame.to_gbq()* and *pandas.read_gbq()* signature and documentation to reflect changes from the pandas-gbq library version 0.4.0. Adds intersphinx mapping to pandas-gbq library. (GH20564)
- Added new writer for exporting Stata dta files in version 117, `StataWriter117`. This format supports exporting strings with lengths up to 2,000,000 characters (GH16450)
- `to_hdf()` and *read_hdf()* now accept an `errors` keyword argument to control encoding error handling (GH20835)
- *cut()* has gained the `duplicates='raise'|'drop'` option to control whether to raise on duplicated edges (GH20947)
- *date_range()*, *timedelta_range()*, and *interval_range()* now return a linearly spaced index if `start`, `stop`, and `periods` are specified, but `freq` is not. (GH20808, GH20983, GH20976)

Backwards incompatible API changes

Dependencies have increased minimum versions

We have updated our minimum supported versions of dependencies (GH15184). If installed, we now require:

Package	Minimum Version	Required	Issue
python-dateutil	2.5.0	X	GH15184
openpyxl	2.4.0		GH15184
beautifulsoup4	4.2.1		GH20082
setuptools	24.2.0		GH20698

Instantiation from dicts preserves dict insertion order for Python 3.6+

Until Python 3.6, dicts in Python had no formally defined ordering. For Python version 3.6 and later, dicts are ordered by insertion order, see PEP 468. pandas will use the dict's insertion order, when creating a `Series` or `DataFrame` from a dict and you're using Python version 3.6 or higher. (GH19884)

Previous behavior (and current behavior if on Python < 3.6):

```
In [16]: pd.Series({'Income': 2000,
   ....:            'Expenses': -1500,
   ....:            'Taxes': -200,
   ....:            'Net result': 300})
Out[16]:
Expenses     -1500
Income        2000
Net result     300
Taxes         -200
dtype: int64
```

Note the Series above is ordered alphabetically by the index values.

New behavior (for Python >= 3.6):

```
In [74]: pd.Series({'Income': 2000,
   ....:            'Expenses': -1500,
   ....:            'Taxes': -200,
   ....:            'Net result': 300})
   ....:
Out[74]:
Income        2000
Expenses     -1500
Taxes         -200
Net result     300
Length: 4, dtype: int64
```

Notice that the Series is now ordered by insertion order. This new behavior is used for all relevant pandas types (`Series`, `DataFrame`, `SparseSeries` and `SparseDataFrame`).

If you wish to retain the old behavior while using Python >= 3.6, you can use `.sort_index()`:

```
In [75]: pd.Series({'Income': 2000,
   ....:            'Expenses': -1500,
   ....:            'Taxes': -200,
```

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```
   ....:             'Net result': 300}).sort_index()
   ....:
Out[75]:
Expenses     -1500
Income        2000
Net result     300
Taxes         -200
Length: 4, dtype: int64
```

Deprecate Panel

`Panel` was deprecated in the 0.20.x release, showing as a `DeprecationWarning`. Using `Panel` will now show a `FutureWarning`. The recommended way to represent 3-D data are with a `MultiIndex` on a `DataFrame` via the `to_frame()` or with the xarray package. pandas provides a `to_xarray()` method to automate this conversion (GH13563, GH18324).

```
In [75]: import pandas._testing as tm

In [76]: p = tm.makePanel()

In [77]: p
Out[77]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

Convert to a MultiIndex DataFrame

```
In [78]: p.to_frame()
Out[78]:
                     ItemA     ItemB     ItemC
major      minor
2000-01-03 A      0.469112  0.721555  0.404705
           B     -1.135632  0.271860 -1.039268
           C      0.119209  0.276232 -1.344312
           D     -2.104569  0.113648 -0.109050
2000-01-04 A     -0.282863 -0.706771  0.577046
           B      1.212112 -0.424972 -0.370647
           C     -1.044236 -1.087401  0.844885
           D     -0.494929 -1.478427  1.643563
2000-01-05 A     -1.509059 -1.039575 -1.715002
           B     -0.173215  0.567020 -1.157892
           C     -0.861849 -0.673690  1.075770
           D      1.071804  0.524988 -1.469388

[12 rows x 3 columns]
```

Convert to an xarray DataArray

```
In [79]: p.to_xarray()
Out[79]:
<xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)>
```

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```
array([[[ 0.469112, -1.135632,  0.119209, -2.104569],
        [-0.282863,  1.212112, -1.044236, -0.494929],
        [-1.509059, -0.173215, -0.861849,  1.071804]],

       [[ 0.721555,  0.27186 ,  0.276232,  0.113648],
        [-0.706771, -0.424972, -1.087401, -1.478427],
        [-1.039575,  0.56702 , -0.67369 ,  0.524988]],

       [[ 0.404705, -1.039268, -1.344312, -0.10905 ],
        [ 0.577046, -0.370647,  0.844885,  1.643563],
        [-1.715002, -1.157892,  1.07577 , -1.469388]]])
Coordinates:
  * items       (items) object 'ItemA' 'ItemB' 'ItemC'
  * major_axis  (major_axis) datetime64[ns] 2000-01-03 2000-01-04 2000-01-05
  * minor_axis  (minor_axis) object 'A' 'B' 'C' 'D'
```

pandas.core.common removals

The following error & warning messages are removed from `pandas.core.common` (GH13634, GH19769):

- `PerformanceWarning`
- `UnsupportedFunctionCall`
- `UnsortedIndexError`
- `AbstractMethodError`

These are available from import from `pandas.errors` (since 0.19.0).

Changes to make output of `DataFrame.apply` consistent

`DataFrame.apply()` was inconsistent when applying an arbitrary user-defined-function that returned a list-like with `axis=1`. Several bugs and inconsistencies are resolved. If the applied function returns a Series, then pandas will return a DataFrame; otherwise a Series will be returned, this includes the case where a list-like (e.g. `tuple` or `list` is returned) (GH16353, GH17437, GH17970, GH17348, GH17892, GH18573, GH17602, GH18775, GH18901, GH18919).

```
In [76]: df = pd.DataFrame(np.tile(np.arange(3), 6).reshape(6, -1) + 1,
   ....:                   columns=['A', 'B', 'C'])
   ....:

In [77]: df
Out[77]:
   A  B  C
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

[6 rows x 3 columns]
```

Previous behavior: if the returned shape happened to match the length of original columns, this would return a `DataFrame`. If the return shape did not match, a `Series` with lists was returned.

```
In [3]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[3]:
   A  B  C
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

In [4]: df.apply(lambda x: [1, 2], axis=1)
Out[4]:
0    [1, 2]
1    [1, 2]
2    [1, 2]
3    [1, 2]
4    [1, 2]
5    [1, 2]
dtype: object
```

New behavior: When the applied function returns a list-like, this will now *always* return a `Series`.

```
In [78]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[78]:
0    [1, 2, 3]
1    [1, 2, 3]
2    [1, 2, 3]
3    [1, 2, 3]
4    [1, 2, 3]
5    [1, 2, 3]
Length: 6, dtype: object

In [79]: df.apply(lambda x: [1, 2], axis=1)
Out[79]:
0    [1, 2]
1    [1, 2]
2    [1, 2]
3    [1, 2]
4    [1, 2]
5    [1, 2]
Length: 6, dtype: object
```

To have expanded columns, you can use `result_type='expand'`

```
In [80]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='expand')
Out[80]:
   0  1  2
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

[6 rows x 3 columns]
```

To broadcast the result across the original columns (the old behaviour for list-likes of the correct length), you can use `result_type='broadcast'`. The shape must match the original columns.

```
In [81]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='broadcast')
Out[81]:
   A  B  C
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

[6 rows x 3 columns]
```

Returning a `Series` allows one to control the exact return structure and column names:

```
In [82]: df.apply(lambda x: pd.Series([1, 2, 3], index=['D', 'E', 'F']), axis=1)
Out[82]:
   D  E  F
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

[6 rows x 3 columns]
```

Concatenation will no longer sort

In a future version of pandas *`pandas.concat()`* will no longer sort the non-concatenation axis when it is not already aligned. The current behavior is the same as the previous (sorting), but now a warning is issued when `sort` is not specified and the non-concatenation axis is not aligned (GH4588).

```
In [83]: df1 = pd.DataFrame({"a": [1, 2], "b": [1, 2]}, columns=['b', 'a'])

In [84]: df2 = pd.DataFrame({"a": [4, 5]})

In [85]: pd.concat([df1, df2])
Out[85]:
     b  a
0  1.0  1
1  2.0  2
0  NaN  4
1  NaN  5

[4 rows x 2 columns]
```

To keep the previous behavior (sorting) and silence the warning, pass `sort=True`

```
In [86]: pd.concat([df1, df2], sort=True)
Out[86]:
   a    b
0  1  1.0
1  2  2.0
0  4  NaN
1  5  NaN
```

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```
[4 rows x 2 columns]
```

To accept the future behavior (no sorting), pass `sort=False`

Note that this change also applies to *`DataFrame.append()`*, which has also received a `sort` keyword for controlling this behavior.

Build changes

- Building pandas for development now requires `cython >= 0.24` (GH18613)
- Building from source now explicitly requires `setuptools` in `setup.py` (GH18113)
- Updated conda recipe to be in compliance with conda-build 3.0+ (GH18002)

Index division by zero fills correctly

Division operations on `Index` and subclasses will now fill division of positive numbers by zero with `np.inf`, division of negative numbers by zero with `-np.inf` and `0 / 0` with `np.nan`. This matches existing `Series` behavior. (GH19322, GH19347)

Previous behavior:

```
In [6]: index = pd.Int64Index([-1, 0, 1])

In [7]: index / 0
Out[7]: Int64Index([0, 0, 0], dtype='int64')

# Previous behavior yielded different results depending on the type of zero in the␣
↪divisor
In [8]: index / 0.0
Out[8]: Float64Index([-inf, nan, inf], dtype='float64')

In [9]: index = pd.UInt64Index([0, 1])

In [10]: index / np.array([0, 0], dtype=np.uint64)
Out[10]: UInt64Index([0, 0], dtype='uint64')

In [11]: pd.RangeIndex(1, 5) / 0
ZeroDivisionError: integer division or modulo by zero
```

Current behavior:

```
In [87]: index = pd.Int64Index([-1, 0, 1])

# division by zero gives -infinity where negative,
# +infinity where positive, and NaN for 0 / 0
In [88]: index / 0
Out[88]: Float64Index([-inf, nan, inf], dtype='float64')

# The result of division by zero should not depend on
# whether the zero is int or float
In [89]: index / 0.0
Out[89]: Float64Index([-inf, nan, inf], dtype='float64')
```

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```
In [90]: index = pd.UInt64Index([0, 1])

In [91]: index / np.array([0, 0], dtype=np.uint64)
Out[91]: Float64Index([nan, inf], dtype='float64')

In [92]: pd.RangeIndex(1, 5) / 0
Out[92]: Float64Index([inf, inf, inf, inf], dtype='float64')
```

Extraction of matching patterns from strings

By default, extracting matching patterns from strings with `str.extract()` used to return a `Series` if a single group was being extracted (a `DataFrame` if more than one group was extracted). As of pandas 0.23.0 `str.extract()` always returns a `DataFrame`, unless `expand` is set to `False`. Finally, `None` was an accepted value for the `expand` parameter (which was equivalent to `False`), but now raises a `ValueError`. (GH11386)

Previous behavior:

```
In [1]: s = pd.Series(['number 10', '12 eggs'])

In [2]: extracted = s.str.extract(r'.*(\d\d).*')

In [3]: extracted
Out [3]:
0    10
1    12
dtype: object

In [4]: type(extracted)
Out [4]:
pandas.core.series.Series
```

New behavior:

```
In [93]: s = pd.Series(['number 10', '12 eggs'])

In [94]: extracted = s.str.extract(r'.*(\d\d).*')

In [95]: extracted
Out[95]:
    0
0  10
1  12

[2 rows x 1 columns]

In [96]: type(extracted)
Out[96]: pandas.core.frame.DataFrame
```

To restore previous behavior, simply set `expand` to `False`:

```
In [97]: s = pd.Series(['number 10', '12 eggs'])

In [98]: extracted = s.str.extract(r'.*(\d\d).*', expand=False)
```

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```
In [99]: extracted
Out[99]:
0    10
1    12
Length: 2, dtype: object

In [100]: type(extracted)
Out[100]: pandas.core.series.Series
```

Default value for the `ordered` parameter of `CategoricalDtype`

The default value of the `ordered` parameter for `CategoricalDtype` has changed from `False` to `None` to allow updating of `categories` without impacting `ordered`. Behavior should remain consistent for downstream objects, such as *`Categorical`* (GH18790)

In previous versions, the default value for the `ordered` parameter was `False`. This could potentially lead to the `ordered` parameter unintentionally being changed from `True` to `False` when users attempt to update `categories` if `ordered` is not explicitly specified, as it would silently default to `False`. The new behavior for `ordered=None` is to retain the existing value of `ordered`.

New behavior:

```
In [2]: from pandas.api.types import CategoricalDtype

In [3]: cat = pd.Categorical(list('abcaba'), ordered=True, categories=list('cba'))

In [4]: cat
Out[4]:
[a, b, c, a, b, a]
Categories (3, object): [c < b < a]

In [5]: cdt = CategoricalDtype(categories=list('cbad'))

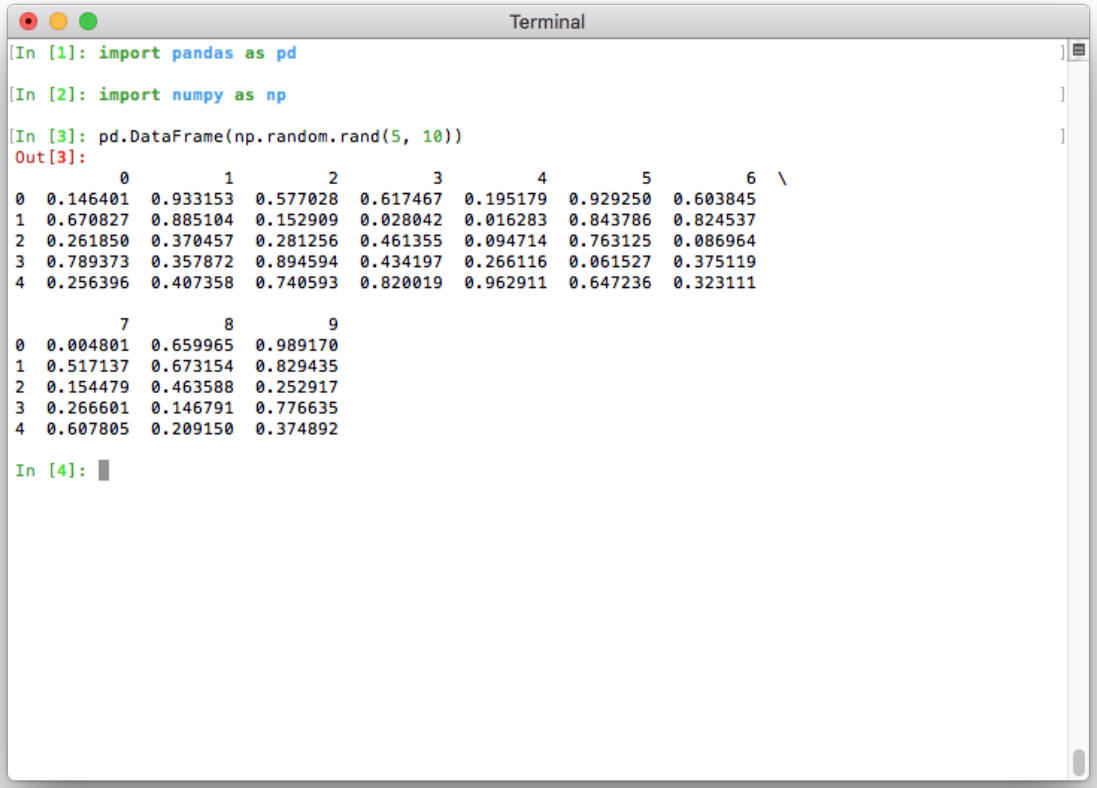
In [6]: cat.astype(cdt)
Out[6]:
[a, b, c, a, b, a]
Categories (4, object): [c < b < a < d]
```

Notice in the example above that the converted `Categorical` has retained `ordered=True`. Had the default value for `ordered` remained as `False`, the converted `Categorical` would have become unordered, despite `ordered=False` never being explicitly specified. To change the value of `ordered`, explicitly pass it to the new dtype, e.g. `CategoricalDtype(categories=list('cbad'), ordered=False)`.

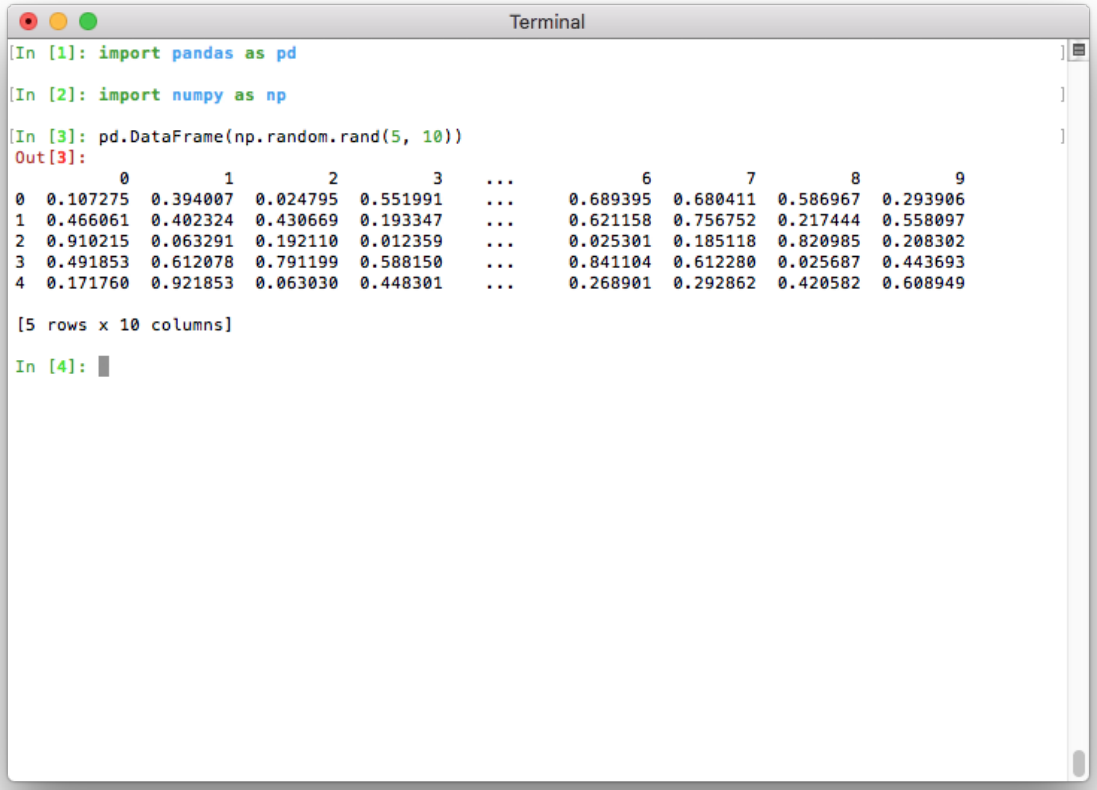
Note that the unintentional conversion of `ordered` discussed above did not arise in previous versions due to separate bugs that prevented `astype` from doing any type of category to category conversion (GH10696, GH18593). These bugs have been fixed in this release, and motivated changing the default value of `ordered`.

Better pretty-printing of DataFrames in a terminal

Previously, the default value for the maximum number of columns was `pd.options.display.max_columns=20`. This meant that relatively wide data frames would not fit within the terminal width, and pandas would introduce line breaks to display these 20 columns. This resulted in an output that was relatively difficult to read:



If Python runs in a terminal, the maximum number of columns is now determined automatically so that the printed data frame fits within the current terminal width (`pd.options.display.max_columns=0`) (GH17023). If Python runs as a Jupyter kernel (such as the Jupyter QtConsole or a Jupyter notebook, as well as in many IDEs), this value cannot be inferred automatically and is thus set to `20` as in previous versions. In a terminal, this results in a much nicer output:



Note that if you don't like the new default, you can always set this option yourself. To revert to the old setting, you can run this line:

```
pd.options.display.max_columns = 20
```

Datetimelike API changes

- The default `Timedelta` constructor now accepts an `ISO 8601 Duration` string as an argument (GH19040)
- Subtracting `NaT` from a *`Series`* with `dtype='datetime64[ns]'` returns a `Series` with `dtype='timedelta64[ns]'` instead of `dtype='datetime64[ns]'` (GH18808)
- Addition or subtraction of `NaT` from *`TimedeltaIndex`* will return `TimedeltaIndex` instead of `DatetimeIndex` (GH19124)
- `DatetimeIndex.shift()` and `TimedeltaIndex.shift()` will now raise `NullFrequencyError` (which subclasses `ValueError`, which was raised in older versions) when the index object frequency is `None` (GH19147)
- Addition and subtraction of `NaN` from a *`Series`* with `dtype='timedelta64[ns]'` will raise a `TypeError` instead of treating the `NaN` as `NaT` (GH19274)
- `NaT` division with `datetime.timedelta` will now return `NaN` instead of raising (GH17876)

- Operations between a *Series* with dtype `dtype='datetime64[ns]'` and a *PeriodIndex* will correctly raises `TypeError` (GH18850)
- Subtraction of *Series* with timezone-aware `dtype='datetime64[ns]'` with mismatched timezones will raise `TypeError` instead of `ValueError` (GH18817)
- *Timestamp* will no longer silently ignore unused or invalid `tz` or `tzinfo` keyword arguments (GH17690)
- *Timestamp* will no longer silently ignore invalid `freq` arguments (GH5168)
- `CacheableOffset` and `WeekDay` are no longer available in the `pandas.tseries.offsets` module (GH17830)
- `pandas.tseries.frequencies.get_freq_group()` and `pandas.tseries.frequencies.DAYS` are removed from the public API (GH18034)
- *Series.truncate()* and *DataFrame.truncate()* will raise a `ValueError` if the index is not sorted instead of an unhelpful `KeyError` (GH17935)
- *Series.first* and *DataFrame.first* will now raise a `TypeError` rather than `NotImplementedError` when index is not a *DatetimeIndex* (GH20725).
- *Series.last* and *DataFrame.last* will now raise a `TypeError` rather than `NotImplementedError` when index is not a *DatetimeIndex* (GH20725).
- Restricted `DateOffset` keyword arguments. Previously, `DateOffset` subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. (GH17176, GH18226).
- *pandas.merge()* provides a more informative error message when trying to merge on timezone-aware and timezone-naive columns (GH15800)
- For *DatetimeIndex* and *TimedeltaIndex* with `freq=None`, addition or subtraction of integer-dtyped array or `Index` will raise `NullFrequencyError` instead of `TypeError` (GH19895)
- *Timestamp* constructor now accepts a `nanosecond` keyword or positional argument (GH18898)
- *DatetimeIndex* will now raise an `AttributeError` when the `tz` attribute is set after instantiation (GH3746)
- *DatetimeIndex* with a `pytz` timezone will now return a consistent `pytz` timezone (GH18595)

Other API changes

- *Series.astype()* and *Index.astype()* with an incompatible dtype will now raise a `TypeError` rather than a `ValueError` (GH18231)
- `Series` construction with an `object` dtyped tz-aware datetime and `dtype=object` specified, will now return an `object` dtyped `Series`, previously this would infer the datetime dtype (GH18231)
- A *Series* of `dtype=category` constructed from an empty `dict` will now have categories of `dtype=object` rather than `dtype=float64`, consistently with the case in which an empty list is passed (GH18515)
- All-NaN levels in a `MultiIndex` are now assigned `float` rather than `object` dtype, promoting consistency with `Index` (GH17929).
- Levels names of a `MultiIndex` (when not None) are now required to be unique: trying to create a `MultiIndex` with repeated names will raise a `ValueError` (GH18872)
- Both construction and renaming of `Index`/`MultiIndex` with non-hashable `name`/`names` will now raise `TypeError` (GH20527)

- *Index.map()* can now accept Series and dictionary input objects (GH12756, GH18482, GH18509).
- *DataFrame.unstack()* will now default to filling with np.nan for object columns. (GH12815)
- *IntervalIndex* constructor will raise if the closed parameter conflicts with how the input data is inferred to be closed (GH18421)
- Inserting missing values into indexes will work for all types of indexes and automatically insert the correct type of missing value (NaN, NaT, etc.) regardless of the type passed in (GH18295)
- When created with duplicate labels, MultiIndex now raises a ValueError. (GH17464)
- *Series.fillna()* now raises a TypeError instead of a ValueError when passed a list, tuple or DataFrame as a value (GH18293)
- *pandas.DataFrame.merge()* no longer casts a float column to object when merging on int and float columns (GH16572)
- *pandas.merge()* now raises a ValueError when trying to merge on incompatible data types (GH9780)
- The default NA value for *UInt64Index* has changed from 0 to NaN, which impacts methods that mask with NA, such as UInt64Index.where() (GH18398)
- Refactored setup.py to use find_packages instead of explicitly listing out all subpackages (GH18535)
- Rearranged the order of keyword arguments in *read_excel()* to align with *read_csv()* (GH16672)
- *wide_to_long()* previously kept numeric-like suffixes as object dtype. Now they are cast to numeric if possible (GH17627)
- In *read_excel()*, the comment argument is now exposed as a named parameter (GH18735)
- Rearranged the order of keyword arguments in *read_excel()* to align with *read_csv()* (GH16672)
- The options html.border and mode.use_inf_as_null were deprecated in prior versions, these will now show FutureWarning rather than a DeprecationWarning (GH19003)
- *IntervalIndex* and IntervalDtype no longer support categorical, object, and string subtypes (GH19016)
- IntervalDtype now returns True when compared against 'interval' regardless of subtype, and IntervalDtype.name now returns 'interval' regardless of subtype (GH18980)
- KeyError now raises instead of ValueError in *drop()*, drop(), *drop()*, *drop()* when dropping a non-existent element in an axis with duplicates (GH19186)
- *Series.to_csv()* now accepts a compression argument that works in the same way as the compression argument in *DataFrame.to_csv()* (GH18958)
- Set operations (union, difference...) on *IntervalIndex* with incompatible index types will now raise a TypeError rather than a ValueError (GH19329)
- DateOffset objects render more simply, e.g. <DateOffset: days=1> instead of <DateOffset: kwds={'days': 1}> (GH19403)
- Categorical.fillna now validates its value and method keyword arguments. It now raises when both or none are specified, matching the behavior of *Series.fillna()* (GH19682)
- pd.to_datetime('today') now returns a datetime, consistent with pd.Timestamp('today'); previously pd.to_datetime('today') returned a .normalized() datetime (GH19935)
- *Series.str.replace()* now takes an optional regex keyword which, when set to False, uses literal string replacement rather than regex replacement (GH16808)
- *DatetimeIndex.strftime()* and *PeriodIndex.strftime()* now return an Index instead of a numpy array to be consistent with similar accessors (GH20127)

- Constructing a Series from a list of length 1 no longer broadcasts this list when a longer index is specified (GH19714, GH20391).
- *DataFrame.to_dict()* with `orient='index'` no longer casts int columns to float for a DataFrame with only int and float columns (GH18580)
- A user-defined-function that is passed to `Series.rolling().aggregate()`, `DataFrame.rolling().aggregate()`, or its expanding cousins, will now *always* be passed a `Series`, rather than a `np.array`; `.apply()` only has the `raw` keyword, see *here*. This is consistent with the signatures of `.aggregate()` across pandas (GH20584)
- Rolling and Expanding types raise `NotImplementedError` upon iteration (GH11704).

Deprecations

- `Series.from_array` and `SparseSeries.from_array` are deprecated. Use the normal constructor `Series(..)` and `SparseSeries(..)` instead (GH18213).
- `DataFrame.as_matrix` is deprecated. Use `DataFrame.values` instead (GH18458).
- `Series.asobject`, `DatetimeIndex.asobject`, `PeriodIndex.asobject` and `TimeDeltaIndex.asobject` have been deprecated. Use `.astype(object)` instead (GH18572)
- Grouping by a tuple of keys now emits a `FutureWarning` and is deprecated. In the future, a tuple passed to `'by'` will always refer to a single key that is the actual tuple, instead of treating the tuple as multiple keys. To retain the previous behavior, use a list instead of a tuple (GH18314)
- `Series.valid` is deprecated. Use *Series.dropna()* instead (GH18800).
- *read_excel()* has deprecated the `skip_footer` parameter. Use `skipfooter` instead (GH18836)
- *ExcelFile.parse()* has deprecated `sheetname` in favor of `sheet_name` for consistency with *read_excel()* (GH20920).
- The `is_copy` attribute is deprecated and will be removed in a future version (GH18801).
- `IntervalIndex.from_intervals` is deprecated in favor of the *IntervalIndex* constructor (GH19263)
- `DataFrame.from_items` is deprecated. Use *DataFrame.from_dict()* instead, or `DataFrame.from_dict(OrderedDict())` if you wish to preserve the key order (GH17320, GH17312)
- Indexing a *MultiIndex* or a `FloatIndex` with a list containing some missing keys will now show a `FutureWarning`, which is consistent with other types of indexes (GH17758).
- The `broadcast` parameter of `.apply()` is deprecated in favor of `result_type='broadcast'` (GH18577)
- The `reduce` parameter of `.apply()` is deprecated in favor of `result_type='reduce'` (GH18577)
- The `order` parameter of *factorize()* is deprecated and will be removed in a future release (GH19727)
- `Timestamp.weekday_name`, `DatetimeIndex.weekday_name`, and `Series.dt.weekday_name` are deprecated in favor of *Timestamp.day_name()*, *DatetimeIndex.day_name()*, and *Series.dt.day_name()* (GH12806)
- `pandas.tseries.plotting.tsplot` is deprecated. Use *Series.plot()* instead (GH18627)
- `Index.summary()` is deprecated and will be removed in a future version (GH18217)
- `NDFrame.get_ftype_counts()` is deprecated and will be removed in a future version (GH18243)

- The `convert_datetime64` parameter in *DataFrame.to_records()* has been deprecated and will be removed in a future version. The NumPy bug motivating this parameter has been resolved. The default value for this parameter has also changed from `True` to `None` (GH18160).
- `Series.rolling().apply()`, `DataFrame.rolling().apply()`, `Series.expanding().apply()`, and `DataFrame.expanding().apply()` have deprecated passing an `np.array` by default. One will need to pass the new `raw` parameter to be explicit about what is passed (GH20584)
- The `data`, `base`, `strides`, `flags` and `itemsize` properties of the `Series` and `Index` classes have been deprecated and will be removed in a future version (GH20419).
- `DatetimeIndex.offset` is deprecated. Use `DatetimeIndex.freq` instead (GH20716)
- Floor division between an integer ndarray and a *Timedelta* is deprecated. Divide by *Timedelta.value* instead (GH19761)
- Setting `PeriodIndex.freq` (which was not guaranteed to work correctly) is deprecated. Use *PeriodIndex.asfreq()* instead (GH20678)
- `Index.get_duplicates()` is deprecated and will be removed in a future version (GH20239)
- The previous default behavior of negative indices in `Categorical.take` is deprecated. In a future version it will change from meaning missing values to meaning positional indices from the right. The future behavior is consistent with *Series.take()* (GH20664).
- Passing multiple axes to the `axis` parameter in *DataFrame.dropna()* has been deprecated and will be removed in a future version (GH20987)

Removal of prior version deprecations/changes

- Warnings against the obsolete usage `Categorical(codes, categories)`, which were emitted for instance when the first two arguments to `Categorical()` had different dtypes, and recommended the use of `Categorical.from_codes`, have now been removed (GH8074)
- The `levels` and `labels` attributes of a `MultiIndex` can no longer be set directly (GH4039).
- `pd.tseries.util.pivot_annual` has been removed (deprecated since v0.19). Use `pivot_table` instead (GH18370)
- `pd.tseries.util.isleapyear` has been removed (deprecated since v0.19). Use `.is_leap_year` property in Datetime-likes instead (GH18370)
- `pd.ordered_merge` has been removed (deprecated since v0.19). Use `pd.merge_ordered` instead (GH18459)
- The `SparseList` class has been removed (GH14007)
- The `pandas.io.wb` and `pandas.io.data` stub modules have been removed (GH13735)
- `Categorical.from_array` has been removed (GH13854)
- The `freq` and `how` parameters have been removed from the `rolling`/`expanding`/`ewm` methods of DataFrame and Series (deprecated since v0.18). Instead, resample before calling the methods. (GH18601 & GH18668)
- `DatetimeIndex.to_datetime`, `Timestamp.to_datetime`, `PeriodIndex.to_datetime`, and `Index.to_datetime` have been removed (GH8254, GH14096, GH14113)
- *read_csv()* has dropped the `skip_footer` parameter (GH13386)
- *read_csv()* has dropped the `as_recarray` parameter (GH13373)
- *read_csv()* has dropped the `buffer_lines` parameter (GH13360)

- *read_csv()* has dropped the compact_ints and use_unsigned parameters (GH13323)
- The Timestamp class has dropped the offset attribute in favor of freq (GH13593)
- The Series, Categorical, and Index classes have dropped the reshape method (GH13012)
- pandas.tseries.frequencies.get_standard_freq has been removed in favor of pandas.tseries.frequencies.to_offset(freq).rule_code (GH13874)
- The freqstr keyword has been removed from pandas.tseries.frequencies.to_offset in favor of freq (GH13874)
- The Panel4D and PanelND classes have been removed (GH13776)
- The Panel class has dropped the to_long and toLong methods (GH19077)
- The options display.line_with and display.height are removed in favor of display.width and display.max_rows respectively (GH4391, GH19107)
- The labels attribute of the Categorical class has been removed in favor of *Categorical.codes* (GH7768)
- The flavor parameter have been removed from func:*to_sql* method (GH13611)
- The modules pandas.tools.hashing and pandas.util.hashing have been removed (GH16223)
- The top-level functions pd.rolling_*, pd.expanding_* and pd.ewm* have been removed (Deprecated since v0.18). Instead, use the DataFrame/Series methods *rolling*, *expanding* and *ewm* (GH18723)
- Imports from pandas.core.common for functions such as is_datetime64_dtype are now removed. These are located in pandas.api.types. (GH13634, GH19769)
- The infer_dst keyword in *Series.tz_localize()*, *DatetimeIndex.tz_localize()* and *DatetimeIndex* have been removed. infer_dst=True is equivalent to ambiguous='infer', and infer_dst=False to ambiguous='raise' (GH7963).
- When .resample() was changed from an eager to a lazy operation, like .groupby() in v0.18.0, we put in place compatibility (with a FutureWarning), so operations would continue to work. This is now fully removed, so a Resampler will no longer forward compat operations (GH20554)
- Remove long deprecated axis=None parameter from .replace() (GH20271)

Performance improvements

- Indexers on Series or DataFrame no longer create a reference cycle (GH17956)
- Added a keyword argument, cache, to *to_datetime()* that improved the performance of converting duplicate datetime arguments (GH11665)
- DateOffset arithmetic performance is improved (GH18218)
- Converting a Series of Timedelta objects to days, seconds, etc... sped up through vectorization of underlying methods (GH18092)
- Improved performance of .map() with a Series/dict input (GH15081)
- The overridden Timedelta properties of days, seconds and microseconds have been removed, leveraging their built-in Python versions instead (GH18242)
- Series construction will reduce the number of copies made of the input data in certain cases (GH17449)
- Improved performance of *Series.dt.date()* and *DatetimeIndex.date()* (GH18058)
- Improved performance of *Series.dt.time()* and *DatetimeIndex.time()* (GH18461)

- Improved performance of `IntervalIndex.symmetric_difference()` (GH18475)
- Improved performance of `DatetimeIndex` and `Series` arithmetic operations with Business-Month and Business-Quarter frequencies (GH18489)
- *`Series()`* / *`DataFrame()`* tab completion limits to 100 values, for better performance. (GH18587)
- Improved performance of *`DataFrame.median()`* with `axis=1` when bottleneck is not installed (GH16468)
- Improved performance of *`MultiIndex.get_loc()`* for large indexes, at the cost of a reduction in performance for small ones (GH18519)
- Improved performance of *`MultiIndex.remove_unused_levels()`* when there are no unused levels, at the cost of a reduction in performance when there are (GH19289)
- Improved performance of *`Index.get_loc()`* for non-unique indexes (GH19478)
- Improved performance of pairwise `.rolling()` and `.expanding()` with `.cov()` and `.corr()` operations (GH17917)
- Improved performance of *`pandas.core.groupby.GroupBy.rank()`* (GH15779)
- Improved performance of variable `.rolling()` on `.min()` and `.max()` (GH19521)
- Improved performance of *`pandas.core.groupby.GroupBy.ffill()`* and *`pandas.core.groupby.GroupBy.bfill()`* (GH11296)
- Improved performance of *`pandas.core.groupby.GroupBy.any()`* and *`pandas.core.groupby.GroupBy.all()`* (GH15435)
- Improved performance of *`pandas.core.groupby.GroupBy.pct_change()`* (GH19165)
- Improved performance of *`Series.isin()`* in the case of categorical dtypes (GH20003)
- Improved performance of `getattr(Series, attr)` when the Series has certain index types. This manifested in slow printing of large Series with a `DatetimeIndex` (GH19764)
- Fixed a performance regression for `GroupBy.nth()` and `GroupBy.last()` with some object columns (GH19283)
- Improved performance of `pandas.core.arrays.Categorical.from_codes()` (GH18501)

Documentation changes

Thanks to all of the contributors who participated in the pandas Documentation Sprint, which took place on March 10th. We had about 500 participants from over 30 locations across the world. You should notice that many of the *API docstrings* have greatly improved.

There were too many simultaneous contributions to include a release note for each improvement, but this GitHub search should give you an idea of how many docstrings were improved.

Special thanks to Marc Garcia for organizing the sprint. For more information, read the NumFOCUS blogpost recapping the sprint.

- Changed spelling of "numpy" to "NumPy", and "python" to "Python". (GH19017)
- Consistency when introducing code samples, using either colon or period. Rewrote some sentences for greater clarity, added more dynamic references to functions, methods and classes. (GH18941, GH18948, GH18973, GH19017)
- Added a reference to *`DataFrame.assign()`* in the concatenate section of the merging documentation (GH18665)

Bug fixes

Categorical

Warning: A class of bugs were introduced in pandas 0.21 with `CategoricalDtype` that affects the correctness of operations like `merge`, `concat`, and indexing when comparing multiple unordered `Categorical` arrays that have the same categories, but in a different order. We highly recommend upgrading or manually aligning your categories before doing these operations.

- Bug in `Categorical.equals` returning the wrong result when comparing two unordered `Categorical` arrays with the same categories, but in a different order (GH16603)
- Bug in *pandas.api.types.union_categoricals()* returning the wrong result when for unordered categoricals with the categories in a different order. This affected *pandas.concat()* with Categorical data (GH19096).
- Bug in *pandas.merge()* returning the wrong result when joining on an unordered `Categorical` that had the same categories but in a different order (GH19551)
- Bug in `CategoricalIndex.get_indexer()` returning the wrong result when `target` was an unordered `Categorical` that had the same categories as `self` but in a different order (GH19551)
- Bug in *Index.astype()* with a categorical dtype where the resultant index is not converted to a *CategoricalIndex* for all types of index (GH18630)
- Bug in *Series.astype()* and `Categorical.astype()` where an existing categorical data does not get updated (GH10696, GH18593)
- Bug in *Series.str.split()* with `expand=True` incorrectly raising an IndexError on empty strings (GH20002).
- Bug in *Index* constructor with `dtype=CategoricalDtype(...)` where `categories` and `ordered` are not maintained (GH19032)
- Bug in *Series* constructor with scalar and `dtype=CategoricalDtype(...)` where `categories` and `ordered` are not maintained (GH19565)
- Bug in `Categorical.__iter__` not converting to Python types (GH19909)
- Bug in *pandas.factorize()* returning the unique codes for the `uniques`. This now returns a `Categorical` with the same dtype as the input (GH19721)
- Bug in *pandas.factorize()* including an item for missing values in the `uniques` return value (GH19721)
- Bug in *Series.take()* with categorical data interpreting `-1` in `indices` as missing value markers, rather than the last element of the Series (GH20664)

Datetimelike

- Bug in `Series.__sub__()` subtracting a non-nanosecond `np.datetime64` object from a `Series` gave incorrect results (GH7996)
- Bug in *`DatetimeIndex`*, *`TimedeltaIndex`* addition and subtraction of zero-dimensional integer arrays gave incorrect results (GH19012)
- Bug in *`DatetimeIndex`* and *`TimedeltaIndex`* where adding or subtracting an array-like of `DateOffset` objects either raised (`np.array`, `pd.Index`) or broadcast incorrectly (`pd.Series`) (GH18849)
- Bug in `Series.__add__()` adding Series with dtype `timedelta64[ns]` to a timezone-aware `DatetimeIndex` incorrectly dropped timezone information (GH13905)
- Adding a `Period` object to a `datetime` or `Timestamp` object will now correctly raise a `TypeError` (GH17983)
- Bug in *`Timestamp`* where comparison with an array of `Timestamp` objects would result in a `RecursionError` (GH15183)
- Bug in *`Series`* floor-division where operating on a scalar `timedelta` raises an exception (GH18846)
- Bug in *`DatetimeIndex`* where the repr was not showing high-precision time values at the end of a day (e.g., 23:59:59.999999999) (GH19030)
- Bug in `.astype()` to non-ns timedelta units would hold the incorrect dtype (GH19176, GH19223, GH12425)
- Bug in subtracting *`Series`* from `NaT` incorrectly returning `NaT` (GH19158)
- Bug in *`Series.truncate()`* which raises `TypeError` with a monotonic `PeriodIndex` (GH17717)
- Bug in *`pct_change()`* using `periods` and `freq` returned different length outputs (GH7292)
- Bug in comparison of *`DatetimeIndex`* against `None` or `datetime.date` objects raising `TypeError` for `==` and `!=` comparisons instead of all-`False` and all-`True`, respectively (GH19301)
- Bug in *`Timestamp`* and *`to_datetime()`* where a string representing a barely out-of-bounds timestamp would be incorrectly rounded down instead of raising `OutOfBoundsDatetime` (GH19382)
- Bug in *`Timestamp.floor()`* *`DatetimeIndex.floor()`* where time stamps far in the future and past were not rounded correctly (GH19206)
- Bug in *`to_datetime()`* where passing an out-of-bounds datetime with `errors='coerce'` and `utc=True` would raise `OutOfBoundsDatetime` instead of parsing to `NaT` (GH19612)
- Bug in *`DatetimeIndex`* and *`TimedeltaIndex`* addition and subtraction where name of the returned object was not always set consistently. (GH19744)
- Bug in *`DatetimeIndex`* and *`TimedeltaIndex`* addition and subtraction where operations with numpy arrays raised `TypeError` (GH19847)
- Bug in *`DatetimeIndex`* and *`TimedeltaIndex`* where setting the `freq` attribute was not fully supported (GH20678)

Timedelta

- Bug in `Timedelta.__mul__()` where multiplying by `NaT` returned `NaT` instead of raising a `TypeError` (GH19819)
- Bug in *Series* with `dtype='timedelta64[ns]'` where addition or subtraction of `TimedeltaIndex` had results cast to `dtype='int64'` (GH17250)
- Bug in *Series* with `dtype='timedelta64[ns]'` where addition or subtraction of `TimedeltaIndex` could return a `Series` with an incorrect name (GH19043)
- Bug in `Timedelta.__floordiv__()` and `Timedelta.__rfloordiv__()` dividing by many incompatible numpy objects was incorrectly allowed (GH18846)
- Bug where dividing a scalar timedelta-like object with *TimedeltaIndex* performed the reciprocal operation (GH19125)
- Bug in *TimedeltaIndex* where division by a `Series` would return a `TimedeltaIndex` instead of a `Series` (GH19042)
- Bug in `Timedelta.__add__()`, `Timedelta.__sub__()` where adding or subtracting a `np.timedelta64` object would return another `np.timedelta64` instead of a `Timedelta` (GH19738)
- Bug in `Timedelta.__floordiv__()`, `Timedelta.__rfloordiv__()` where operating with a `Tick` object would raise a `TypeError` instead of returning a numeric value (GH19738)
- Bug in *Period.asfreq()* where periods near `datetime(1, 1, 1)` could be converted incorrectly (GH19643, GH19834)
- Bug in *Timedelta.total_seconds()* causing precision errors, for example `Timedelta('30S').total_seconds()==30.000000000000004` (GH19458)
- Bug in `Timedelta.__rmod__()` where operating with a `numpy.timedelta64` returned a `timedelta64` object instead of a `Timedelta` (GH19820)
- Multiplication of *TimedeltaIndex* by `TimedeltaIndex` will now raise `TypeError` instead of raising `ValueError` in cases of length mismatch (GH19333)
- Bug in indexing a *TimedeltaIndex* with a `np.timedelta64` object which was raising a `TypeError` (GH20393)

Timezones

- Bug in creating a `Series` from an array that contains both tz-naive and tz-aware values will result in a `Series` whose dtype is tz-aware instead of object (GH16406)
- Bug in comparison of timezone-aware *DatetimeIndex* against `NaT` incorrectly raising `TypeError` (GH19276)
- Bug in `DatetimeIndex.astype()` when converting between timezone aware dtypes, and converting from timezone aware to naive (GH18951)
- Bug in comparing *DatetimeIndex*, which failed to raise `TypeError` when attempting to compare timezone-aware and timezone-naive datetimelike objects (GH18162)
- Bug in localization of a naive, datetime string in a `Series` constructor with a `datetime64[ns, tz]` dtype (GH174151)
- *Timestamp.replace()* will now handle Daylight Savings transitions gracefully (GH18319)
- Bug in tz-aware *DatetimeIndex* where addition/subtraction with a *TimedeltaIndex* or array with `dtype='timedelta64[ns]'` was incorrect (GH17558)

- Bug in `DatetimeIndex.insert()` where inserting `NaT` into a timezone-aware index incorrectly raised (GH16357)
- Bug in *DataFrame* constructor, where tz-aware Datetimeindex and a given column name will result in an empty `DataFrame` (GH19157)
- Bug in *Timestamp.tz_localize()* where localizing a timestamp near the minimum or maximum valid values could overflow and return a timestamp with an incorrect nanosecond value (GH12677)
- Bug when iterating over *DatetimeIndex* that was localized with fixed timezone offset that rounded nanosecond precision to microseconds (GH19603)
- Bug in *DataFrame.diff()* that raised an `IndexError` with tz-aware values (GH18578)
- Bug in *melt()* that converted tz-aware dtypes to tz-naive (GH15785)
- Bug in `Dataframe.count()` that raised an `ValueError`, if `Dataframe.dropna()` was called for a single column with timezone-aware values. (GH13407)

Offsets

- Bug in `WeekOfMonth` and `Week` where addition and subtraction did not roll correctly (GH18510, GH18672, GH18864)
- Bug in `WeekOfMonth` and `LastWeekOfMonth` where default keyword arguments for constructor raised `ValueError` (GH19142)
- Bug in `FY5253Quarter`, `LastWeekOfMonth` where rollback and rollforward behavior was inconsistent with addition and subtraction behavior (GH18854)
- Bug in `FY5253` where `datetime` addition and subtraction incremented incorrectly for dates on the year-end but not normalized to midnight (GH18854)
- Bug in `FY5253` where date offsets could incorrectly raise an `AssertionError` in arithmetic operations (GH14774)

Numeric

- Bug in *Series* constructor with an int or float list where specifying `dtype=str`, `dtype='str'` or `dtype='U'` failed to convert the data elements to strings (GH16605)
- Bug in *Index* multiplication and division methods where operating with a `Series` would return an `Index` object instead of a `Series` object (GH19042)
- Bug in the *DataFrame* constructor in which data containing very large positive or very large negative numbers was causing `OverflowError` (GH18584)
- Bug in *Index* constructor with `dtype='uint64'` where int-like floats were not coerced to *UInt64Index* (GH18400)
- Bug in *DataFrame* flex arithmetic (e.g. `df.add(other, fill_value=foo)`) with a `fill_value` other than `None` failed to raise `NotImplementedError` in corner cases where either the frame or `other` has length zero (GH19522)
- Multiplication and division of numeric-dtyped *Index* objects with timedelta-like scalars returns `TimedeltaIndex` instead of raising `TypeError` (GH19333)
- Bug where `NaN` was returned instead of 0 by *Series.pct_change()* and *DataFrame.pct_change()* when `fill_method` is not `None` (GH19873)

Strings

- Bug in *Series.str.get()* with a dictionary in the values and the index not in the keys, raising KeyError (GH20671)

Indexing

- Bug in *Index* construction from list of mixed type tuples (GH18505)
- Bug in *Index.drop()* when passing a list of both tuples and non-tuples (GH18304)
- Bug in *DataFrame.drop()*, Panel.drop(), *Series.drop()*, *Index.drop()* where no KeyError is raised when dropping a non-existent element from an axis that contains duplicates (GH19186)
- Bug in indexing a datetimelike Index that raised ValueError instead of IndexError (GH18386).
- *Index.to_series()* now accepts index and name kwargs (GH18699)
- *DatetimeIndex.to_series()* now accepts index and name kwargs (GH18699)
- Bug in indexing non-scalar value from Series having non-unique Index will return value flattened (GH17610)
- Bug in indexing with iterator containing only missing keys, which raised no error (GH20748)
- Fixed inconsistency in .ix between list and scalar keys when the index has integer dtype and does not include the desired keys (GH20753)
- Bug in __setitem__ when indexing a *DataFrame* with a 2-d boolean ndarray (GH18582)
- Bug in str.extractall when there were no matches empty *Index* was returned instead of appropriate *MultiIndex* (GH19034)
- Bug in *IntervalIndex* where empty and purely NA data was constructed inconsistently depending on the construction method (GH18421)
- Bug in IntervalIndex.symmetric_difference() where the symmetric difference with a non-IntervalIndex did not raise (GH18475)
- Bug in *IntervalIndex* where set operations that returned an empty IntervalIndex had the wrong dtype (GH19101)
- Bug in *DataFrame.drop_duplicates()* where no KeyError is raised when passing in columns that don't exist on the DataFrame (GH19726)
- Bug in Index subclasses constructors that ignore unexpected keyword arguments (GH19348)
- Bug in *Index.difference()* when taking difference of an Index with itself (GH20040)
- Bug in *DataFrame.first_valid_index()* and *DataFrame.last_valid_index()* in presence of entire rows of NaNs in the middle of values (GH20499).
- Bug in *IntervalIndex* where some indexing operations were not supported for overlapping or non-monotonic uint64 data (GH20636)
- Bug in Series.is_unique where extraneous output in stderr is shown if Series contains objects with __ne__ defined (GH20661)
- Bug in .loc assignment with a single-element list-like incorrectly assigns as a list (GH19474)
- Bug in partial string indexing on a Series/DataFrame with a monotonic decreasing DatetimeIndex (GH19362)
- Bug in performing in-place operations on a DataFrame with a duplicate Index (GH17105)

- Bug in *IntervalIndex.get_loc()* and *IntervalIndex.get_indexer()* when used with an *IntervalIndex* containing a single interval (GH17284, GH20921)
- Bug in `.loc` with a `uint64` indexer (GH20722)

MultiIndex

- Bug in `MultiIndex.__contains__()` where non-tuple keys would return `True` even if they had been dropped (GH19027)
- Bug in `MultiIndex.set_labels()` which would cause casting (and potentially clipping) of the new labels if the `level` argument is not 0 or a list like [0, 1, ...] (GH19057)
- Bug in *MultiIndex.get_level_values()* which would return an invalid index on level of ints with missing values (GH17924)
- Bug in `MultiIndex.unique()` when called on empty *MultiIndex* (GH20568)
- Bug in `MultiIndex.unique()` which would not preserve level names (GH20570)
- Bug in *MultiIndex.remove_unused_levels()* which would fill nan values (GH18417)
- Bug in *MultiIndex.from_tuples()* which would fail to take zipped tuples in python3 (GH18434)
- Bug in *MultiIndex.get_loc()* which would fail to automatically cast values between float and int (GH18818, GH15994)
- Bug in *MultiIndex.get_loc()* which would cast boolean to integer labels (GH19086)
- Bug in *MultiIndex.get_loc()* which would fail to locate keys containing `NaN` (GH18485)
- Bug in *MultiIndex.get_loc()* in large *MultiIndex*, would fail when levels had different dtypes (GH18520)
- Bug in indexing where nested indexers having only numpy arrays are handled incorrectly (GH19686)

IO

- *read_html()* now rewinds seekable IO objects after parse failure, before attempting to parse with a new parser. If a parser errors and the object is non-seekable, an informative error is raised suggesting the use of a different parser (GH17975)
- *DataFrame.to_html()* now has an option to add an id to the leading `<table>` tag (GH8496)
- Bug in `read_msgpack()` with a non existent file is passed in Python 2 (GH15296)
- Bug in *read_csv()* where a `MultiIndex` with duplicate columns was not being mangled appropriately (GH18062)
- Bug in *read_csv()* where missing values were not being handled properly when `keep_default_na=False` with dictionary `na_values` (GH19227)
- Bug in *read_csv()* causing heap corruption on 32-bit, big-endian architectures (GH20785)
- Bug in *read_sas()* where a file with 0 variables gave an `AttributeError` incorrectly. Now it gives an `EmptyDataError` (GH18184)
- Bug in *DataFrame.to_latex()* where pairs of braces meant to serve as invisible placeholders were escaped (GH18667)
- Bug in *DataFrame.to_latex()* where a `NaN` in a `MultiIndex` would cause an `IndexError` or incorrect output (GH14249)

- Bug in *DataFrame.to_latex()* where a non-string index-level name would result in an AttributeError (GH19981)
- Bug in *DataFrame.to_latex()* where the combination of an index name and the index_names=False option would result in incorrect output (GH18326)
- Bug in *DataFrame.to_latex()* where a MultiIndex with an empty string as its name would result in incorrect output (GH18669)
- Bug in *DataFrame.to_latex()* where missing space characters caused wrong escaping and produced non-valid latex in some cases (GH20859)
- Bug in *read_json()* where large numeric values were causing an OverflowError (GH18842)
- Bug in *DataFrame.to_parquet()* where an exception was raised if the write destination is S3 (GH19134)
- *Interval* now supported in *DataFrame.to_excel()* for all Excel file types (GH19242)
- *Timedelta* now supported in *DataFrame.to_excel()* for all Excel file types (GH19242, GH9155, GH19900)
- Bug in *pandas.io.stata.StataReader.value_labels()* raising an AttributeError when called on very old files. Now returns an empty dict (GH19417)
- Bug in *read_pickle()* when unpickling objects with *TimedeltaIndex* or *Float64Index* created with pandas prior to version 0.20 (GH19939)
- Bug in pandas.io.json.json_normalize() where sub-records are not properly normalized if any sub-records values are NoneType (GH20030)
- Bug in usecols parameter in *read_csv()* where error is not raised correctly when passing a string. (GH20529)
- Bug in *HDFStore.keys()* when reading a file with a soft link causes exception (GH20523)
- Bug in HDFStore.select_column() where a key which is not a valid store raised an AttributeError instead of a KeyError (GH17912)

Plotting

- Better error message when attempting to plot but matplotlib is not installed (GH19810).
- *DataFrame.plot()* now raises a ValueError when the x or y argument is improperly formed (GH18671)
- Bug in *DataFrame.plot()* when x and y arguments given as positions caused incorrect referenced columns for line, bar and area plots (GH20056)
- Bug in formatting tick labels with datetime.time() and fractional seconds (GH18478).
- *Series.plot.kde()* has exposed the args ind and bw_method in the docstring (GH18461). The argument ind may now also be an integer (number of sample points).
- *DataFrame.plot()* now supports multiple columns to the y argument (GH19699)

GroupBy/resample/rolling

- Bug when grouping by a single column and aggregating with a class like `list` or `tuple` (GH18079)
- Fixed regression in *`DataFrame.groupby()`* which would not emit an error when called with a tuple key not in the index (GH18798)
- Bug in *`DataFrame.resample()`* which silently ignored unsupported (or mistyped) options for `label`, `closed` and `convention` (GH19303)
- Bug in *`DataFrame.groupby()`* where tuples were interpreted as lists of keys rather than as keys (GH17979, GH18249)
- Bug in *`DataFrame.groupby()`* where aggregation by `first`/`last`/`min`/`max` was causing timestamps to lose precision (GH19526)
- Bug in *`DataFrame.transform()`* where particular aggregation functions were being incorrectly cast to match the dtype(s) of the grouped data (GH19200)
- Bug in *`DataFrame.groupby()`* passing the `on=` kwarg, and subsequently using `.apply()` (GH17813)
- Bug in *`DataFrame.resample().aggregate`* not raising a `KeyError` when aggregating a non-existent column (GH16766, GH19566)
- Bug in `DataFrameGroupBy.cumsum()` and `DataFrameGroupBy.cumprod()` when `skipna` was passed (GH19806)
- Bug in *`DataFrame.resample()`* that dropped timezone information (GH13238)
- Bug in *`DataFrame.groupby()`* where transformations using `np.all` and `np.any` were raising a `ValueError` (GH20653)
- Bug in *`DataFrame.resample()`* where `ffill`, `bfill`, `pad`, `backfill`, `fillna`, `interpolate`, and `asfreq` were ignoring `loffset`. (GH20744)
- Bug in *`DataFrame.groupby()`* when applying a function that has mixed data types and the user supplied function can fail on the grouping column (GH20949)
- Bug in `DataFrameGroupBy.rolling().apply()` where operations performed against the associated `DataFrameGroupBy` object could impact the inclusion of the grouped item(s) in the result (GH14013)

Sparse

- Bug in which creating a `SparseDataFrame` from a dense `Series` or an unsupported type raised an uncontrolled exception (GH19374)
- Bug in `SparseDataFrame.to_csv` causing exception (GH19384)
- Bug in `SparseSeries.memory_usage` which caused segfault by accessing non sparse elements (GH19368)
- Bug in constructing a `SparseArray`: if `data` is a scalar and `index` is defined it will coerce to `float64` regardless of scalar's dtype. (GH19163)

Reshaping

- Bug in *DataFrame.merge()* where referencing a CategoricalIndex by name, where the by kwarg would KeyError (GH20777)
- Bug in *DataFrame.stack()* which fails trying to sort mixed type levels under Python 3 (GH18310)
- Bug in *DataFrame.unstack()* which casts int to float if columns is a MultiIndex with unused levels (GH17845)
- Bug in *DataFrame.unstack()* which raises an error if index is a MultiIndex with unused labels on the unstacked level (GH18562)
- Fixed construction of a *Series* from a dict containing NaN as key (GH18480)
- Fixed construction of a *DataFrame* from a dict containing NaN as key (GH18455)
- Disabled construction of a *Series* where len(index) > len(data) = 1, which previously would broadcast the data item, and now raises a ValueError (GH18819)
- Suppressed error in the construction of a *DataFrame* from a dict containing scalar values when the corresponding keys are not included in the passed index (GH18600)
- Fixed (changed from object to float64) dtype of *DataFrame* initialized with axes, no data, and dtype=int (GH19646)
- Bug in *Series.rank()* where Series containing NaT modifies the Series inplace (GH18521)
- Bug in *cut()* which fails when using readonly arrays (GH18773)
- Bug in *DataFrame.pivot_table()* which fails when the aggfunc arg is of type string. The behavior is now consistent with other methods like agg and apply (GH18713)
- Bug in *DataFrame.merge()* in which merging using Index objects as vectors raised an Exception (GH19038)
- Bug in *DataFrame.stack()*, *DataFrame.unstack()*, *Series.unstack()* which were not returning subclasses (GH15563)
- Bug in timezone comparisons, manifesting as a conversion of the index to UTC in .concat() (GH18523)
- Bug in *concat()* when concatenating sparse and dense series it returns only a SparseDataFrame. Should be a DataFrame. (GH18914, GH18686, and GH16874)
- Improved error message for *DataFrame.merge()* when there is no common merge key (GH19427)
- Bug in *DataFrame.join()* which does an outer instead of a left join when being called with multiple DataFrames and some have non-unique indices (GH19624)
- *Series.rename()* now accepts axis as a kwarg (GH18589)
- Bug in *rename()* where an Index of same-length tuples was converted to a MultiIndex (GH19497)
- Comparisons between *Series* and *Index* would return a Series with an incorrect name, ignoring the Index's name attribute (GH19582)
- Bug in *qcut()* where datetime and timedelta data with NaT present raised a ValueError (GH19768)
- Bug in *DataFrame.iterrows()*, which would infers strings not compliant to ISO8601 to datetimes (GH19671)
- Bug in *Series* constructor with Categorical where a ValueError is not raised when an index of different length is given (GH19342)
- Bug in *DataFrame.astype()* where column metadata is lost when converting to categorical or a dictionary of dtypes (GH19920)

- Bug in `cut()` and `qcut()` where timezone information was dropped (GH19872)
- Bug in `Series` constructor with a `dtype=str`, previously raised in some cases (GH19853)
- Bug in `get_dummies()`, and `select_dtypes()`, where duplicate column names caused incorrect behavior (GH20848)
- Bug in `isna()`, which cannot handle ambiguous typed lists (GH20675)
- Bug in `concat()` which raises an error when concatenating TZ-aware dataframes and all-NaT dataframes (GH12396)
- Bug in `concat()` which raises an error when concatenating empty TZ-aware series (GH18447)

Other

- Improved error message when attempting to use a Python keyword as an identifier in a `numexpr` backed query (GH18221)
- Bug in accessing a `pandas.get_option()`, which raised `KeyError` rather than `OptionError` when looking up a non-existent option key in some cases (GH19789)
- Bug in `testing.assert_series_equal()` and `testing.assert_frame_equal()` for Series or DataFrames with differing unicode data (GH20503)

Contributors

A total of 328 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- dajcs +
- deflatSOCO +
- derestle-htwg
- discort
- dmanikowski-reef +
- donK23 +
- elrubio +
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- fjdiod
- fjetter +
- froessler +
- gabrielclow
- gfyoung
- ghasemnaddaf
- h-vetinari +
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- ignamv +
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- sfoo +
- stefansimik +
- stonebig
- tmnhat2001 +
- tomneep +
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5.7 Version 0.22

5.7.1 Version 0.22.0 (December 29, 2017)

This is a major release from 0.21.1 and includes a single, API-breaking change. We recommend that all users upgrade to this version after carefully reading the release note (singular!).

Backwards incompatible API changes

pandas 0.22.0 changes the handling of empty and all-*NA* sums and products. The summary is that

- The sum of an empty or all-*NA* `Series` is now `0`
- The product of an empty or all-*NA* `Series` is now `1`
- We've added a `min_count` parameter to `.sum()` and `.prod()` controlling the minimum number of valid values for the result to be valid. If fewer than `min_count` non-*NA* values are present, the result is *NA*. The default is `0`. To return `NaN`, the 0.21 behavior, use `min_count=1`.

Some background: In pandas 0.21, we fixed a long-standing inconsistency in the return value of all-*NA* series depending on whether or not bottleneck was installed. See *Sum/prod of all-NaN or empty Series/DataFrames is now consistently NaN*. At the same time, we changed the sum and prod of an empty `Series` to also be `NaN`.

Based on feedback, we've partially reverted those changes.

Arithmetic operations

The default sum for empty or all-*NA* `Series` is now `0`.

pandas 0.21.x

```
In [1]: pd.Series([]).sum()
Out[1]: nan

In [2]: pd.Series([np.nan]).sum()
Out[2]: nan
```

pandas 0.22.0

```
In [1]: pd.Series([]).sum()
Out[1]: 0.0

In [2]: pd.Series([np.nan]).sum()
Out[2]: 0.0
```

The default behavior is the same as pandas 0.20.3 with bottleneck installed. It also matches the behavior of NumPy's `np.nansum` on empty and all-*NA* arrays.

To have the sum of an empty series return `NaN` (the default behavior of pandas 0.20.3 without bottleneck, or pandas 0.21.x), use the `min_count` keyword.

```
In [3]: pd.Series([]).sum(min_count=1)
Out[3]: nan
```

Thanks to the `skipna` parameter, the `.sum` on an all-*NA* series is conceptually the same as the `.sum` of an empty one with `skipna=True` (the default).

```
In [4]: pd.Series([np.nan]).sum(min_count=1)  # skipna=True by default
Out[4]: nan
```

The `min_count` parameter refers to the minimum number of *non-null* values required for a non-NA sum or product.

`Series.prod()` has been updated to behave the same as *`Series.sum()`*, returning `1` instead.

```
In [5]: pd.Series([]).prod()
Out[5]: 1.0

In [6]: pd.Series([np.nan]).prod()
Out[6]: 1.0

In [7]: pd.Series([]).prod(min_count=1)
Out[7]: nan
```

These changes affect *`DataFrame.sum()`* and *`DataFrame.prod()`* as well. Finally, a few less obvious places in pandas are affected by this change.

Grouping by a Categorical

Grouping by a `Categorical` and summing now returns `0` instead of `NaN` for categories with no observations. The product now returns `1` instead of `NaN`.

pandas 0.21.x

```
In [8]: grouper = pd.Categorical(['a', 'a'], categories=['a', 'b'])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out[9]:
a    3.0
b    NaN
dtype: float64
```

pandas 0.22

```
In [8]: grouper = pd.Categorical(["a", "a"], categories=["a", "b"])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out[9]:
a    3
b    0
Length: 2, dtype: int64
```

To restore the 0.21 behavior of returning `NaN` for unobserved groups, use `min_count>=1`.

```
In [10]: pd.Series([1, 2]).groupby(grouper).sum(min_count=1)
Out[10]:
a    3.0
b    NaN
Length: 2, dtype: float64
```

Resample

The sum and product of all-*NA* bins has changed from `NaN` to `0` for sum and `1` for product.

pandas 0.21.x

```
In [11]: s = pd.Series([1, 1, np.nan, np.nan],
   ....:               index=pd.date_range('2017', periods=4))
   ....: s
Out[11]:
2017-01-01    1.0
2017-01-02    1.0
2017-01-03    NaN
2017-01-04    NaN
Freq: D, dtype: float64

In [12]: s.resample('2d').sum()
Out[12]:
2017-01-01    2.0
2017-01-03    NaN
Freq: 2D, dtype: float64
```

pandas 0.22.0

```
In [11]: s = pd.Series([1, 1, np.nan, np.nan], index=pd.date_range("2017", periods=4))

In [12]: s.resample("2d").sum()
Out[12]:
2017-01-01    2.0
2017-01-03    0.0
Freq: 2D, Length: 2, dtype: float64
```

To restore the 0.21 behavior of returning `NaN`, use `min_count>=1`.

```
In [13]: s.resample("2d").sum(min_count=1)
Out[13]:
2017-01-01    2.0
2017-01-03    NaN
Freq: 2D, Length: 2, dtype: float64
```

In particular, upsampling and taking the sum or product is affected, as upsampling introduces missing values even if the original series was entirely valid.

pandas 0.21.x

```
In [14]: idx = pd.DatetimeIndex(['2017-01-01', '2017-01-02'])

In [15]: pd.Series([1, 2], index=idx).resample('12H').sum()
Out[15]:
2017-01-01 00:00:00    1.0
2017-01-01 12:00:00    NaN
2017-01-02 00:00:00    2.0
Freq: 12H, dtype: float64
```

pandas 0.22.0

```
In [14]: idx = pd.DatetimeIndex(["2017-01-01", "2017-01-02"])

In [15]: pd.Series([1, 2], index=idx).resample("12H").sum()
Out[15]:
2017-01-01 00:00:00    1
2017-01-01 12:00:00    0
2017-01-02 00:00:00    2
Freq: 12H, Length: 3, dtype: int64
```

Once again, the `min_count` keyword is available to restore the 0.21 behavior.

```
In [16]: pd.Series([1, 2], index=idx).resample("12H").sum(min_count=1)
Out[16]:
2017-01-01 00:00:00    1.0
2017-01-01 12:00:00    NaN
2017-01-02 00:00:00    2.0
Freq: 12H, Length: 3, dtype: float64
```

Rolling and expanding

Rolling and expanding already have a `min_periods` keyword that behaves similar to `min_count`. The only case that changes is when doing a rolling or expanding sum with `min_periods=0`. Previously this returned `NaN`, when fewer than `min_periods` non-*NA* values were in the window. Now it returns `0`.

pandas 0.21.1

```
In [17]: s = pd.Series([np.nan, np.nan])

In [18]: s.rolling(2, min_periods=0).sum()
Out[18]:
0   NaN
1   NaN
dtype: float64
```

pandas 0.22.0

```
In [17]: s = pd.Series([np.nan, np.nan])

In [18]: s.rolling(2, min_periods=0).sum()
Out[18]:
0    0.0
1    0.0
Length: 2, dtype: float64
```

The default behavior of `min_periods=None`, implying that `min_periods` equals the window size, is unchanged.

Compatibility

If you maintain a library that should work across pandas versions, it may be easiest to exclude pandas 0.21 from your requirements. Otherwise, all your `sum()` calls would need to check if the `Series` is empty before summing.

With setuptools, in your `setup.py` use:

```
install_requires=['pandas!=0.21.*', ...]
```

With conda, use

```
requirements:
  run:
    - pandas !=0.21.0,!=0.21.1
```

Note that the inconsistency in the return value for all-*NA* series is still there for pandas 0.20.3 and earlier. Avoiding pandas 0.21 will only help with the empty case.

Contributors

A total of 1 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Tom Augspurger

5.8 Version 0.21

5.8.1 Version 0.21.1 (December 12, 2017)

This is a minor bug-fix release in the 0.21.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Temporarily restore matplotlib datetime plotting functionality. This should resolve issues for users who implicitly relied on pandas to plot datetimes with matplotlib. See *here*.
- Improvements to the Parquet IO functions introduced in 0.21.0. See *here*.

What's new in v0.21.1

- *Restore Matplotlib datetime converter registration*
- *New features*
  - *Improvements to the Parquet IO functionality*
  - *Other enhancements*
- *Deprecations*
- *Performance improvements*
- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *IO*
  - *Plotting*
  - *GroupBy/resample/rolling*
  - *Reshaping*
  - *Numeric*
  - *Categorical*
  - *String*
- *Contributors*

Restore Matplotlib datetime converter registration

pandas implements some matplotlib converters for nicely formatting the axis labels on plots with `datetime` or `Period` values. Prior to pandas 0.21.0, these were implicitly registered with matplotlib, as a side effect of `import pandas`.

In pandas 0.21.0, we required users to explicitly register the converter. This caused problems for some users who relied on those converters being present for regular `matplotlib.pyplot` plotting methods, so we're temporarily reverting that change; pandas 0.21.1 again registers the converters on import, just like before 0.21.0.

We've added a new option to control the converters: `pd.options.plotting.matplotlib.register_converters`. By default, they are registered. Toggling this to `False` removes pandas' formatters and restore any converters we overwrote when registering them (GH18301).

We're working with the matplotlib developers to make this easier. We're trying to balance user convenience (automatically registering the converters) with import performance and best practices (importing pandas shouldn't have the side effect of overwriting any custom converters you've already set). In the future we hope to have most of the datetime formatting functionality in matplotlib, with just the pandas-specific converters in pandas. We'll then gracefully deprecate the automatic registration of converters in favor of users explicitly registering them when they want them.

New features

Improvements to the Parquet IO functionality

- *DataFrame.to_parquet()* will now write non-default indexes when the underlying engine supports it. The indexes will be preserved when reading back in with *read_parquet()* (GH18581).
- *read_parquet()* now allows to specify the columns to read from a parquet file (GH18154)
- *read_parquet()* now allows to specify kwargs which are passed to the respective engine (GH18216)

Other enhancements

- *Timestamp.timestamp()* is now available in Python 2.7. (GH17329)
- *Grouper* and `TimeGrouper` now have a friendly repr output (GH18203).

Deprecations

- `pandas.tseries.register` has been renamed to *pandas.plotting.register_matplotlib_converters()* (GH18301)

Performance improvements

- Improved performance of plotting large series/dataframes (GH18236).

Bug fixes

Conversion

- Bug in *TimedeltaIndex* subtraction could incorrectly overflow when NaT is present (GH17791)
- Bug in *DatetimeIndex* subtracting datetimelike from DatetimeIndex could fail to overflow (GH18020)
- Bug in IntervalIndex.copy() when copying and IntervalIndex with non-default closed (GH18339)
- Bug in *DataFrame.to_dict()* where columns of datetime that are tz-aware were not converted to required arrays when used with orient='records', raising TypeError (GH18372)
- Bug in DateTimeIndex and *date_range()* where mismatching tz-aware start and end timezones would not raise an err if end.tzinfo is None (GH18431)
- Bug in *Series.fillna()* which raised when passed a long integer on Python 2 (GH18159).

Indexing

- Bug in a boolean comparison of a datetime.datetime and a datetime64[ns] dtype Series (GH17965)
- Bug where a MultiIndex with more than a million records was not raising AttributeError when trying to access a missing attribute (GH18165)
- Bug in *IntervalIndex* constructor when a list of intervals is passed with non-default closed (GH18334)
- Bug in Index.putmask when an invalid mask passed (GH18368)
- Bug in masked assignment of a timedelta64[ns] dtype Series, incorrectly coerced to float (GH18493)

IO

- Bug in class:~*pandas.io.stata.StataReader* not converting date/time columns with display formatting addressed (GH17990). Previously columns with display formatting were normally left as ordinal numbers and not converted to datetime objects.
- Bug in *read_csv()* when reading a compressed UTF-16 encoded file (GH18071)
- Bug in *read_csv()* for handling null values in index columns when specifying na_filter=False (GH5239)
- Bug in *read_csv()* when reading numeric category fields with high cardinality (GH18186)
- Bug in *DataFrame.to_csv()* when the table had MultiIndex columns, and a list of strings was passed in for header (GH5539)
- Bug in parsing integer datetime-like columns with specified format in read_sql (GH17855).
- Bug in DataFrame.to_msgpack() when serializing data of the numpy.bool_ datatype (GH18390)
- Bug in *read_json()* not decoding when reading line delimited JSON from S3 (GH17200)
- Bug in pandas.io.json.json_normalize() to avoid modification of meta (GH18610)
- Bug in to_latex() where repeated MultiIndex values were not printed even though a higher level index differed from the previous row (GH14484)
- Bug when reading NaN-only categorical columns in HDFStore (GH18413)

- Bug in *DataFrame.to_latex()* with `longtable=True` where a latex multicolumn always spanned over three columns (GH17959)

Plotting

- Bug in `DataFrame.plot()` and `Series.plot()` with *DatetimeIndex* where a figure generated by them is not pickleable in Python 3 (GH18439)

GroupBy/resample/rolling

- Bug in `DataFrame.resample(...).apply(...)` when there is a callable that returns different columns (GH15169)
- Bug in `DataFrame.resample(...)` when there is a time change (DST) and resampling frequency is 12h or higher (GH15549)
- Bug in `pd.DataFrameGroupBy.count()` when counting over a datetimelike column (GH13393)
- Bug in `rolling.var` where calculation is inaccurate with a zero-valued array (GH18430)

Reshaping

- Error message in `pd.merge_asof()` for key datatype mismatch now includes datatype of left and right key (GH18068)
- Bug in `pd.concat` when empty and non-empty DataFrames or Series are concatenated (GH18178 GH18187)
- Bug in `DataFrame.filter(...)` when `unicode` is passed as a condition in Python 2 (GH13101)
- Bug when merging empty DataFrames when `np.seterr(divide='raise')` is set (GH17776)

Numeric

- Bug in `pd.Series.rolling.skew()` and `rolling.kurt()` with all equal values has floating issue (GH18044)

Categorical

- Bug in *DataFrame.astype()* where casting to 'category' on an empty `DataFrame` causes a segmentation fault (GH18004)
- Error messages in the testing module have been improved when items have different `CategoricalDtype` (GH18069)
- `CategoricalIndex` can now correctly take a `pd.api.types.CategoricalDtype` as its dtype (GH18116)
- Bug in `Categorical.unique()` returning read-only `codes` array when all categories were `NaN` (GH18051)
- Bug in `DataFrame.groupby(axis=1)` with a `CategoricalIndex` (GH18432)

String

- *Series.str.split()* will now propagate NaN values across all expanded columns instead of None (GH18450)

Contributors

A total of 46 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Alexander Buchkovsky +
- Alexander Michael Schade +
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- Hans +
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- Jan Werkmann +
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- Joris Van den Bossche
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5.8.2 Version 0.21.0 (October 27, 2017)

This is a major release from 0.20.3 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Integration with Apache Parquet, including a new top-level *read_parquet()* function and *DataFrame.to_parquet()* method, see *here*.
- New user-facing `pandas.api.types.CategoricalDtype` for specifying categoricals independent of the data, see *here*.
- The behavior of `sum` and `prod` on all-NaN Series/DataFrames is now consistent and no longer depends on whether bottleneck is installed, and `sum` and `prod` on empty Series now return NaN instead of 0, see *here*.
- Compatibility fixes for pypy, see *here*.
- Additions to the `drop`, `reindex` and `rename` API to make them more consistent, see *here*.
- Addition of the new methods `DataFrame.infer_objects` (see *here*) and `GroupBy.pipe` (see *here*).
- Indexing with a list of labels, where one or more of the labels is missing, is deprecated and will raise a KeyError in a future version, see *here*.

Check the *API Changes* and *deprecations* before updating.

What's new in v0.21.0

- *New features*
  - *Integration with Apache Parquet file format*
  - *Method `infer_objects` type conversion*
  - *Improved warnings when attempting to create columns*
  - *Method `drop` now also accepts index/columns keywords*
  - *Methods `rename`, `reindex` now also accept axis keyword*
  - *`CategoricalDtype` for specifying categoricals*
  - *`GroupBy` objects now have a `pipe` method*
  - *`Categorical.rename_categories` accepts a dict-like*
  - *Other enhancements*
- *Backwards incompatible API changes*
  - *Dependencies have increased minimum versions*
  - *Sum/prod of all-NaN or empty Series/DataFrames is now consistently NaN*
  - *Indexing with a list with missing labels is deprecated*
  - *NA naming changes*
  - *Iteration of Series/Index will now return Python scalars*
  - *Indexing with a Boolean Index*
  - *`PeriodIndex` resampling*
  - *Improved error handling during item assignment in pd.eval*
  - *Dtype conversions*
  - *MultiIndex constructor with a single level*
  - *UTC localization with Series*
  - *Consistency of range functions*
  - *No automatic Matplotlib converters*
  - *Other API changes*
- *Deprecations*
  - *Series.select and DataFrame.select*
  - *Series.argmax and Series.argmin*
- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Documentation changes*
- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *IO*

- *Plotting*
- *GroupBy/resample/rolling*
- *Sparse*
- *Reshaping*
- *Numeric*
- *Categorical*
- *PyPy*
- *Other*

- *Contributors*

New features

Integration with Apache Parquet file format

Integration with Apache Parquet, including a new top-level *read_parquet()* and *DataFrame.to_parquet()* method, see *here* (GH15838, GH17438).

Apache Parquet provides a cross-language, binary file format for reading and writing data frames efficiently. Parquet is designed to faithfully serialize and de-serialize `DataFrame` s, supporting all of the pandas dtypes, including extension dtypes such as datetime with timezones.

This functionality depends on either the pyarrow or fastparquet library. For more details, see *the IO docs on Parquet*.

Method `infer_objects` type conversion

The *DataFrame.infer_objects()* and *Series.infer_objects()* methods have been added to perform dtype inference on object columns, replacing some of the functionality of the deprecated `convert_objects` method. See the documentation *here* for more details. (GH11221)

This method only performs soft conversions on object columns, converting Python objects to native types, but not any coercive conversions. For example:

```
In [1]: df = pd.DataFrame({'A': [1, 2, 3],
   ...:                    'B': np.array([1, 2, 3], dtype='object'),
   ...:                    'C': ['1', '2', '3']})
   ...:

In [2]: df.dtypes
Out[2]:
A     int64
B    object
C    object
Length: 3, dtype: object

In [3]: df.infer_objects().dtypes
Out[3]:
A     int64
B     int64
C    object
Length: 3, dtype: object
```

Note that column 'C' was not converted - only scalar numeric types will be converted to a new type. Other types of conversion should be accomplished using the *to_numeric()* function (or *to_datetime()*, *to_timedelta()*).

```
In [4]: df = df.infer_objects()

In [5]: df['C'] = pd.to_numeric(df['C'], errors='coerce')

In [6]: df.dtypes
Out[6]:
A    int64
B    int64
C    int64
Length: 3, dtype: object
```

Improved warnings when attempting to create columns

New users are often puzzled by the relationship between column operations and attribute access on DataFrame instances (GH7175). One specific instance of this confusion is attempting to create a new column by setting an attribute on the DataFrame:

```
In [1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In [2]: df.two = [4, 5, 6]
```

This does not raise any obvious exceptions, but also does not create a new column:

```
In [3]: df
Out[3]:
    one
0  1.0
1  2.0
2  3.0
```

Setting a list-like data structure into a new attribute now raises a UserWarning about the potential for unexpected behavior. See *Attribute Access*.

Method drop now also accepts index/columns keywords

The *drop()* method has gained index/columns keywords as an alternative to specifying the axis. This is similar to the behavior of reindex (GH12392).

For example:

```
In [7]: df = pd.DataFrame(np.arange(8).reshape(2, 4),
   ...:                   columns=['A', 'B', 'C', 'D'])
   ...:

In [8]: df
Out[8]:
   A  B  C  D
0  0  1  2  3
1  4  5  6  7

[2 rows x 4 columns]
```

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```
In [9]: df.drop(['B', 'C'], axis=1)
Out[9]:
   A  D
0  0  3
1  4  7

[2 rows x 2 columns]

# the following is now equivalent
In [10]: df.drop(columns=['B', 'C'])
Out[10]:
   A  D
0  0  3
1  4  7

[2 rows x 2 columns]
```

Methods `rename`, `reindex` now also accept axis keyword

The *DataFrame.rename()* and *DataFrame.reindex()* methods have gained the `axis` keyword to specify the axis to target with the operation (GH12392).

Here's `rename`:

```
In [11]: df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})

In [12]: df.rename(str.lower, axis='columns')
Out[12]:
   a  b
0  1  4
1  2  5
2  3  6

[3 rows x 2 columns]

In [13]: df.rename(id, axis='index')
Out[13]:
                 A  B
94641213881568   1  4
94641213881600   2  5
94641213881632   3  6

[3 rows x 2 columns]
```

And `reindex`:

```
In [14]: df.reindex(['A', 'B', 'C'], axis='columns')
Out[14]:
   A  B   C
0  1  4 NaN
1  2  5 NaN
2  3  6 NaN

[3 rows x 3 columns]
```

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```
In [15]: df.reindex([0, 1, 3], axis='index')
Out[15]:
     A    B
0  1.0  4.0
1  2.0  5.0
3  NaN  NaN

[3 rows x 2 columns]
```

The "index, columns" style continues to work as before.

```
In [16]: df.rename(index=id, columns=str.lower)
Out[16]:
                 a  b
94641213881568   1  4
94641213881600   2  5
94641213881632   3  6

[3 rows x 2 columns]

In [17]: df.reindex(index=[0, 1, 3], columns=['A', 'B', 'C'])
Out[17]:
     A    B   C
0  1.0  4.0 NaN
1  2.0  5.0 NaN
3  NaN  NaN NaN

[3 rows x 3 columns]
```

We *highly* encourage using named arguments to avoid confusion when using either style.

`CategoricalDtype` for specifying categoricals

`pandas.api.types.CategoricalDtype` has been added to the public API and expanded to include the `categories` and `ordered` attributes. A `CategoricalDtype` can be used to specify the set of categories and orderedness of an array, independent of the data. This can be useful for example, when converting string data to a `Categorical` (GH14711, GH15078, GH16015, GH17643):

```
In [18]: from pandas.api.types import CategoricalDtype

In [19]: s = pd.Series(['a', 'b', 'c', 'a'])  # strings

In [20]: dtype = CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)

In [21]: s.astype(dtype)
Out[21]:
0    a
1    b
2    c
3    a
Length: 4, dtype: category
Categories (4, object): ['a' < 'b' < 'c' < 'd']
```

One place that deserves special mention is in *read_csv()*. Previously, with `dtype={'col': 'category'}`, the returned values and categories would always be strings.

```
In [22]: data = 'A,B\na,1\nb,2\nc,3'

In [23]: pd.read_csv(StringIO(data), dtype={'B': 'category'}).B.cat.categories
Out[23]: Index(['1', '2', '3'], dtype='object')
```

Notice the "object" dtype.

With a `CategoricalDtype` of all numerics, datetimes, or timedeltas, we can automatically convert to the correct type

```
In [24]: dtype = {'B': CategoricalDtype([1, 2, 3])}

In [25]: pd.read_csv(StringIO(data), dtype=dtype).B.cat.categories
Out[25]: Int64Index([1, 2, 3], dtype='int64')
```

The values have been correctly interpreted as integers.

The `.dtype` property of a `Categorical`, `CategoricalIndex` or a `Series` with categorical type will now return an instance of `CategoricalDtype`. While the repr has changed, `str(CategoricalDtype())` is still the string `'category'`. We'll take this moment to remind users that the *preferred* way to detect categorical data is to use *`pandas.api.types.is_categorical_dtype()`*, and not `str(dtype) == 'category'`.

See the *CategoricalDtype docs* for more.

`GroupBy` objects now have a `pipe` method

`GroupBy` objects now have a `pipe` method, similar to the one on `DataFrame` and `Series`, that allow for functions that take a `GroupBy` to be composed in a clean, readable syntax. (GH17871)

For a concrete example on combining `.groupby` and `.pipe` , imagine having a DataFrame with columns for stores, products, revenue and sold quantity. We'd like to do a groupwise calculation of *prices* (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable.

First we set the data:

```
In [26]: import numpy as np

In [27]: n = 1000

In [28]: df = pd.DataFrame({'Store': np.random.choice(['Store_1', 'Store_2'], n),
   ....:                    'Product': np.random.choice(['Product_1',
   ....:                                                 'Product_2',
   ....:                                                 'Product_3'
   ....:                                                 ], n),
   ....:                    'Revenue': (np.random.random(n) * 50 + 10).round(2),
   ....:                    'Quantity': np.random.randint(1, 10, size=n)})
   ....:

In [29]: df.head(2)
Out[29]:
     Store    Product  Revenue  Quantity
0  Store_2  Product_2    32.09         7
1  Store_1  Product_3    14.20         1

[2 rows x 4 columns]
```

Now, to find prices per store/product, we can simply do:

```
In [30]: (df.groupby(['Store', 'Product'])
   ....:     .pipe(lambda grp: grp.Revenue.sum() / grp.Quantity.sum())
   ....:     .unstack().round(2))
   ....:
Out[30]:
Product  Product_1  Product_2  Product_3
Store
Store_1       6.73       6.72       7.14
Store_2       7.59       6.98       7.23

[2 rows x 3 columns]
```

See the *documentation* for more.

`Categorical.rename_categories` accepts a dict-like

rename_categories() now accepts a dict-like argument for `new_categories`. The previous categories are looked up in the dictionary's keys and replaced if found. The behavior of missing and extra keys is the same as in *DataFrame.rename()*.

```
In [31]: c = pd.Categorical(['a', 'a', 'b'])

In [32]: c.rename_categories({"a": "eh", "b": "bee"})
Out[32]:
['eh', 'eh', 'bee']
Categories (2, object): ['eh', 'bee']
```

Warning: To assist with upgrading pandas, `rename_categories` treats `Series` as list-like. Typically, Series are considered to be dict-like (e.g. in `.rename`, `.map`). In a future version of pandas `rename_categories` will change to treat them as dict-like. Follow the warning message's recommendations for writing future-proof code.

```
In [33]: c.rename_categories(pd.Series([0, 1], index=['a', 'c']))
FutureWarning: Treating Series 'new_categories' as a list-like and using the values.
In a future version, 'rename_categories' will treat Series like a dictionary.
For dict-like, use 'new_categories.to_dict()'
For list-like, use 'new_categories.values'.
Out[33]:
[0, 0, 1]
Categories (2, int64): [0, 1]
```

Other enhancements

New functions or methods

- *nearest()* is added to support nearest-neighbor upsampling (GH17496).
- *Index* has added support for a `to_frame` method (GH15230).

New keywords

- Added a `skipna` parameter to *`infer_dtype()`* to support type inference in the presence of missing values (GH17059).
- *`Series.to_dict()`* and *`DataFrame.to_dict()`* now support an `into` keyword which allows you to specify the `collections.Mapping` subclass that you would like returned. The default is `dict`, which is backwards compatible. (GH16122)
- *`Series.set_axis()`* and *`DataFrame.set_axis()`* now support the `inplace` parameter. (GH14636)
- *`Series.to_pickle()`* and *`DataFrame.to_pickle()`* have gained a `protocol` parameter (GH16252). By default, this parameter is set to HIGHEST_PROTOCOL
- *`read_feather()`* has gained the `nthreads` parameter for multi-threaded operations (GH16359)
- *`DataFrame.clip()`* and *`Series.clip()`* have gained an `inplace` argument. (GH15388)
- *`crosstab()`* has gained a `margins_name` parameter to define the name of the row / column that will contain the totals when `margins=True`. (GH15972)
- *`read_json()`* now accepts a `chunksize` parameter that can be used when `lines=True`. If `chunksize` is passed, read_json now returns an iterator which reads in `chunksize` lines with each iteration. (GH17048)
- *`read_json()`* and *`to_json()`* now accept a `compression` argument which allows them to transparently handle compressed files. (GH17798)

Various enhancements

- Improved the import time of pandas by about 2.25x. (GH16764)
- Support for PEP 519 – Adding a file system path protocol on most readers (e.g. *`read_csv()`*) and writers (e.g. *`DataFrame.to_csv()`*) (GH13823).
- Added a `__fspath__` method to `pd.HDFStore`, `pd.ExcelFile`, and `pd.ExcelWriter` to work properly with the file system path protocol (GH13823).
- The `validate` argument for *`merge()`* now checks whether a merge is one-to-one, one-to-many, many-to-one, or many-to-many. If a merge is found to not be an example of specified merge type, an exception of type `MergeError` will be raised. For more, see *here* (GH16270)
- Added support for PEP 518 (`pyproject.toml`) to the build system (GH16745)
- `RangeIndex.append()` now returns a `RangeIndex` object when possible (GH16212)
- *`Series.rename_axis()`* and *`DataFrame.rename_axis()`* with `inplace=True` now return `None` while renaming the axis inplace. (GH15704)
- *`api.types.infer_dtype()`* now infers decimals. (GH15690)
- *`DataFrame.select_dtypes()`* now accepts scalar values for include/exclude as well as list-like. (GH16855)
- *`date_range()`* now accepts 'YS' in addition to 'AS' as an alias for start of year. (GH9313)
- *`date_range()`* now accepts 'Y' in addition to 'A' as an alias for end of year. (GH9313)
- *`DataFrame.add_prefix()`* and *`DataFrame.add_suffix()`* now accept strings containing the '%' character. (GH17151)
- Read/write methods that infer compression (*`read_csv()`*, *`read_table()`*, *`read_pickle()`*, and *`to_pickle()`*) can now infer from path-like objects, such as `pathlib.Path`. (GH17206)

- *read_sas()* now recognizes much more of the most frequently used date (datetime) formats in SAS7BDAT files. (GH15871)
- *DataFrame.items()* and *Series.items()* are now present in both Python 2 and 3 and is lazy in all cases. (GH13918, GH17213)
- *pandas.io.formats.style.Styler.where()* has been implemented as a convenience for *pandas.io.formats.style.Styler.applymap()*. (GH17474)
- `MultiIndex.is_monotonic_decreasing()` has been implemented. Previously returned `False` in all cases. (GH16554)
- *read_excel()* raises `ImportError` with a better message if `xlrd` is not installed. (GH17613)
- *DataFrame.assign()* will preserve the original order of `**kwargs` for Python 3.6+ users instead of sorting the column names. (GH14207)
- *Series.reindex()*, *DataFrame.reindex()*, *Index.get_indexer()* now support list-like argument for `tolerance`. (GH17367)

Backwards incompatible API changes

Dependencies have increased minimum versions

We have updated our minimum supported versions of dependencies (GH15206, GH15543, GH15214). If installed, we now require:

Package	Minimum Version	Required
Numpy	1.9.0	X
Matplotlib	1.4.3	
Scipy	0.14.0	
Bottleneck	1.0.0	

Additionally, support has been dropped for Python 3.4 (GH15251).

Sum/prod of all-NaN or empty Series/DataFrames is now consistently NaN

Note: The changes described here have been partially reverted. See the *v0.22.0 Whatsnew* for more.

The behavior of `sum` and `prod` on all-NaN Series/DataFrames no longer depends on whether bottleneck is installed, and return value of `sum` and `prod` on an empty Series has changed (GH9422, GH15507).

Calling `sum` or `prod` on an empty or all-`NaN` `Series`, or columns of a `DataFrame`, will result in `NaN`. See the *docs*.

```
In [33]: s = pd.Series([np.nan])
```

Previously WITHOUT `bottleneck` installed:

```
In [2]: s.sum()
Out[2]: np.nan
```

Previously WITH `bottleneck`:

```
In [2]: s.sum()
Out[2]: 0.0
```

New behavior, without regard to the bottleneck installation:

```
In [34]: s.sum()
Out[34]: 0.0
```

Note that this also changes the sum of an empty `Series`. Previously this always returned 0 regardless of a `bottleneck` installation:

```
In [1]: pd.Series([]).sum()
Out[1]: 0
```

but for consistency with the all-NaN case, this was changed to return NaN as well:

```
In [35]: pd.Series([]).sum()
Out[35]: 0.0
```

Indexing with a list with missing labels is deprecated

Previously, selecting with a list of labels, where one or more labels were missing would always succeed, returning `NaN` for missing labels. This will now show a `FutureWarning`. In the future this will raise a `KeyError` (GH15747). This warning will trigger on a `DataFrame` or a `Series` for using `.loc[]` or `[[]]` when passing a list-of-labels with at least 1 missing label. See the *deprecation docs*.

```
In [36]: s = pd.Series([1, 2, 3])

In [37]: s
Out[37]:
0    1
1    2
2    3
Length: 3, dtype: int64
```

Previous behavior

```
In [4]: s.loc[[1, 2, 3]]
Out[4]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

Current behavior

```
In [4]: s.loc[[1, 2, 3]]
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
↪listlike

Out[4]:
```

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```
1    2.0
2    3.0
3    NaN
dtype: float64
```

The idiomatic way to achieve selecting potentially not-found elements is via `.reindex()`

```
In [38]: s.reindex([1, 2, 3])
Out[38]:
1    2.0
2    3.0
3    NaN
Length: 3, dtype: float64
```

Selection with all keys found is unchanged.

```
In [39]: s.loc[[1, 2]]
Out[39]:
1    2
2    3
Length: 2, dtype: int64
```

NA naming changes

In order to promote more consistency among the pandas API, we have added additional top-level functions *isna()* and *notna()* that are aliases for *isnull()* and *notnull()*. The naming scheme is now more consistent with methods like `.dropna()` and `.fillna()`. Furthermore in all cases where `.isnull()` and `.notnull()` methods are defined, these have additional methods named `.isna()` and `.notna()`, these are included for classes `Categorical`, `Index`, `Series`, and `DataFrame`. (GH15001).

The configuration option `pd.options.mode.use_inf_as_null` is deprecated, and `pd.options.mode.use_inf_as_na` is added as a replacement.

Iteration of Series/Index will now return Python scalars

Previously, when using certain iteration methods for a `Series` with dtype `int` or `float`, you would receive a `numpy` scalar, e.g. a `np.int64`, rather than a Python `int`. Issue (GH10904) corrected this for `Series.tolist()` and `list(Series)`. This change makes all iteration methods consistent, in particular, for `__iter__()` and `.map()`; note that this only affects int/float dtypes. (GH13236, GH13258, GH14216).

```
In [40]: s = pd.Series([1, 2, 3])

In [41]: s
Out[41]:
0    1
1    2
2    3
Length: 3, dtype: int64
```

Previously:

```
In [2]: type(list(s)[0])
Out[2]: numpy.int64
```

New behavior:

```
In [42]: type(list(s)[0])
Out[42]: int
```

Furthermore this will now correctly box the results of iteration for *DataFrame.to_dict()* as well.

```
In [43]: d = {'a': [1], 'b': ['b']}

In [44]: df = pd.DataFrame(d)
```

Previously:

```
In [8]: type(df.to_dict()['a'][0])
Out[8]: numpy.int64
```

New behavior:

```
In [45]: type(df.to_dict()['a'][0])
Out[45]: int
```

Indexing with a Boolean Index

Previously when passing a boolean `Index` to `.loc`, if the index of the `Series/DataFrame` had `boolean` labels, you would get a label based selection, potentially duplicating result labels, rather than a boolean indexing selection (where `True` selects elements), this was inconsistent how a boolean numpy array indexed. The new behavior is to act like a boolean numpy array indexer. (GH17738)

Previous behavior:

```
In [46]: s = pd.Series([1, 2, 3], index=[False, True, False])

In [47]: s
Out[47]:
False    1
True     2
False    3
Length: 3, dtype: int64
```

```
In [59]: s.loc[pd.Index([True, False, True])]
Out[59]:
True     2
False    1
False    3
True     2
dtype: int64
```

Current behavior

```
In [48]: s.loc[pd.Index([True, False, True])]
Out[48]:
False    1
False    3
Length: 2, dtype: int64
```

Furthermore, previously if you had an index that was non-numeric (e.g. strings), then a boolean Index would raise a `KeyError`. This will now be treated as a boolean indexer.

Previously behavior:

```
In [49]: s = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [50]: s
Out[50]:
a    1
b    2
c    3
Length: 3, dtype: int64
```

```
In [39]: s.loc[pd.Index([True, False, True])]
KeyError: "None of [Index([True, False, True], dtype='object')] are in the [index]"
```

Current behavior

```
In [51]: s.loc[pd.Index([True, False, True])]
Out[51]:
a    1
c    3
Length: 2, dtype: int64
```

`PeriodIndex` resampling

In previous versions of pandas, resampling a `Series`/`DataFrame` indexed by a `PeriodIndex` returned a `DatetimeIndex` in some cases (GH12884). Resampling to a multiplied frequency now returns a `PeriodIndex` (GH15944). As a minor enhancement, resampling a `PeriodIndex` can now handle `NaT` values (GH13224)

Previous behavior:

```
In [1]: pi = pd.period_range('2017-01', periods=12, freq='M')

In [2]: s = pd.Series(np.arange(12), index=pi)

In [3]: resampled = s.resample('2Q').mean()

In [4]: resampled
Out[4]:
2017-03-31     1.0
2017-09-30     5.5
2018-03-31    10.0
Freq: 2Q-DEC, dtype: float64

In [5]: resampled.index
Out[5]: DatetimeIndex(['2017-03-31', '2017-09-30', '2018-03-31'], dtype=
↪'datetime64[ns]', freq='2Q-DEC')
```

New behavior:

```
In [52]: pi = pd.period_range('2017-01', periods=12, freq='M')

In [53]: s = pd.Series(np.arange(12), index=pi)

In [54]: resampled = s.resample('2Q').mean()

In [55]: resampled
```

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```
Out[55]:
2017Q1    2.5
2017Q3    8.5
Freq: 2Q-DEC, Length: 2, dtype: float64

In [56]: resampled.index
Out[56]: PeriodIndex(['2017Q1', '2017Q3'], dtype='period[2Q-DEC]', freq='2Q-DEC')
```

Upsampling and calling `.ohlc()` previously returned a `Series`, basically identical to calling `.asfreq()`. OHLC upsampling now returns a DataFrame with columns `open`, `high`, `low` and `close` (GH13083). This is consistent with downsampling and `DatetimeIndex` behavior.

Previous behavior:

```
In [1]: pi = pd.period_range(start='2000-01-01', freq='D', periods=10)

In [2]: s = pd.Series(np.arange(10), index=pi)

In [3]: s.resample('H').ohlc()
Out[3]:
2000-01-01 00:00    0.0
                   ...
2000-01-10 23:00    NaN
Freq: H, Length: 240, dtype: float64

In [4]: s.resample('M').ohlc()
Out[4]:
         open  high  low  close
2000-01     0     9    0      9
```

New behavior:

```
In [57]: pi = pd.period_range(start='2000-01-01', freq='D', periods=10)

In [58]: s = pd.Series(np.arange(10), index=pi)

In [59]: s.resample('H').ohlc()
Out[59]:
                     open  high  low  close
2000-01-01 00:00      0.0   0.0  0.0    0.0
2000-01-01 01:00      NaN   NaN  NaN    NaN
2000-01-01 02:00      NaN   NaN  NaN    NaN
2000-01-01 03:00      NaN   NaN  NaN    NaN
2000-01-01 04:00      NaN   NaN  NaN    NaN
...                   ...   ...  ...    ...
2000-01-10 19:00      NaN   NaN  NaN    NaN
2000-01-10 20:00      NaN   NaN  NaN    NaN
2000-01-10 21:00      NaN   NaN  NaN    NaN
2000-01-10 22:00      NaN   NaN  NaN    NaN
2000-01-10 23:00      NaN   NaN  NaN    NaN

[240 rows x 4 columns]

In [60]: s.resample('M').ohlc()
Out[60]:
         open  high  low  close
2000-01     0     9    0      9
```

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```
[1 rows x 4 columns]
```

Improved error handling during item assignment in pd.eval

`eval()` will now raise a `ValueError` when item assignment malfunctions, or inplace operations are specified, but there is no item assignment in the expression (GH16732)

```
In [61]: arr = np.array([1, 2, 3])
```

Previously, if you attempted the following expression, you would get a not very helpful error message:

```
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...
IndexError: only integers, slices (`:`), ellipsis (`...`), numpy.newaxis (`None`)
and integer or boolean arrays are valid indices
```

This is a very long way of saying numpy arrays don't support string-item indexing. With this change, the error message is now this:

```
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...
ValueError: Cannot assign expression output to target
```

It also used to be possible to evaluate expressions inplace, even if there was no item assignment:

```
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
Out[4]: 3
```

However, this input does not make much sense because the output is not being assigned to the target. Now, a `ValueError` will be raised when such an input is passed in:

```
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
...
ValueError: Cannot operate inplace if there is no assignment
```

Dtype conversions

Previously assignments, `.where()` and `.fillna()` with a `bool` assignment, would coerce to same the type (e.g. int / float), or raise for datetimelikes. These will now preserve the bools with `object` dtypes. (GH16821).

```
In [62]: s = pd.Series([1, 2, 3])
```

```
In [5]: s[1] = True

In [6]: s
Out[6]:
0    1
1    1
2    3
dtype: int64
```

New behavior

```
In [63]: s[1] = True

In [64]: s
Out[64]:
0       1
1    True
2       3
Length: 3, dtype: object
```

Previously, as assignment to a datetimelike with a non-datetimelike would coerce the non-datetime-like item being assigned (GH14145).

```
In [65]: s = pd.Series([pd.Timestamp('2011-01-01'), pd.Timestamp('2012-01-01')])
```

```
In [1]: s[1] = 1

In [2]: s
Out[2]:
0   2011-01-01 00:00:00.000000000
1   1970-01-01 00:00:00.000000001
dtype: datetime64[ns]
```

These now coerce to `object` dtype.

```
In [66]: s[1] = 1

In [67]: s
Out[67]:
0    2011-01-01 00:00:00
1                      1
Length: 2, dtype: object
```

- Inconsistent behavior in `.where()` with datetimelikes which would raise rather than coerce to `object` (GH16402)
- Bug in assignment against `int64` data with `np.ndarray` with `float64` dtype may keep `int64` dtype (GH14001)

MultiIndex constructor with a single level

The `MultiIndex` constructors no longer squeezes a MultiIndex with all length-one levels down to a regular `Index`. This affects all the `MultiIndex` constructors. (GH17178)

Previous behavior:

```
In [2]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[2]: Index(['a', 'b'], dtype='object')
```

Length 1 levels are no longer special-cased. They behave exactly as if you had length 2+ levels, so a *MultiIndex* is always returned from all of the `MultiIndex` constructors:

```
In [68]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[68]:
MultiIndex([('a',),
            ('b',)],
           )
```

UTC localization with Series

Previously, *to_datetime()* did not localize datetime `Series` data when `utc=True` was passed. Now, *to_datetime()* will correctly localize `Series` with a `datetime64[ns, UTC]` dtype to be consistent with how list-like and `Index` data are handled. (GH6415).

Previous behavior

```
In [69]: s = pd.Series(['20130101 00:00:00'] * 3)
```

```
In [12]: pd.to_datetime(s, utc=True)
Out[12]:
0   2013-01-01
1   2013-01-01
2   2013-01-01
dtype: datetime64[ns]
```

New behavior

```
In [70]: pd.to_datetime(s, utc=True)
Out[70]:
0   2013-01-01 00:00:00+00:00
1   2013-01-01 00:00:00+00:00
2   2013-01-01 00:00:00+00:00
Length: 3, dtype: datetime64[ns, UTC]
```

Additionally, DataFrames with datetime columns that were parsed by *read_sql_table()* and *read_sql_query()* will also be localized to UTC only if the original SQL columns were timezone aware datetime columns.

Consistency of range functions

In previous versions, there were some inconsistencies between the various range functions: *date_range()*, *bdate_range()*, *period_range()*, *timedelta_range()*, and *interval_range()*. (GH17471).

One of the inconsistent behaviors occurred when the `start`, `end` and `period` parameters were all specified, potentially leading to ambiguous ranges. When all three parameters were passed, `interval_range` ignored the `period` parameter, `period_range` ignored the `end` parameter, and the other range functions raised. To promote consistency among the range functions, and avoid potentially ambiguous ranges, `interval_range` and `period_range` will now raise when all three parameters are passed.

Previous behavior:

```
 In [2]: pd.interval_range(start=0, end=4, periods=6)
 Out[2]:
 IntervalIndex([(0, 1], (1, 2], (2, 3]]
               closed='right',
               dtype='interval[int64]')

In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
Out[3]: PeriodIndex(['2017Q1', '2017Q2', '2017Q3', '2017Q4', '2018Q1', '2018Q2'],␣
↪dtype='period[Q-DEC]', freq='Q-DEC')
```

New behavior:

```
In [2]: pd.interval_range(start=0, end=4, periods=6)
---------------------------------------------------------------------------
ValueError: Of the three parameters: start, end, and periods, exactly two must be␣
↪specified

In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
---------------------------------------------------------------------------
ValueError: Of the three parameters: start, end, and periods, exactly two must be␣
↪specified
```

Additionally, the endpoint parameter `end` was not included in the intervals produced by `interval_range`. However, all other range functions include `end` in their output. To promote consistency among the range functions, `interval_range` will now include `end` as the right endpoint of the final interval, except if `freq` is specified in a way which skips `end`.

Previous behavior:

```
In [4]: pd.interval_range(start=0, end=4)
Out[4]:
IntervalIndex([(0, 1], (1, 2], (2, 3]]
              closed='right',
              dtype='interval[int64]')
```

New behavior:

```
In [71]: pd.interval_range(start=0, end=4)
Out[71]:
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4]],
              closed='right',
              dtype='interval[int64]')
```

No automatic Matplotlib converters

pandas no longer registers our `date`, `time`, `datetime`, `datetime64`, and `Period` converters with matplotlib when pandas is imported. Matplotlib plot methods (`plt.plot`, `ax.plot`, ...), will not nicely format the x-axis for `DatetimeIndex` or `PeriodIndex` values. You must explicitly register these methods:

pandas built-in `Series.plot` and `DataFrame.plot` *will* register these converters on first-use (GH17710).

Note: This change has been temporarily reverted in pandas 0.21.1, for more details see *here*.

Other API changes

- The Categorical constructor no longer accepts a scalar for the `categories` keyword. (GH16022)
- Accessing a non-existent attribute on a closed `HDFStore` will now raise an `AttributeError` rather than a `ClosedFileError` (GH16301)
- *`read_csv()`* now issues a `UserWarning` if the `names` parameter contains duplicates (GH17095)
- *`read_csv()`* now treats `'null'` and `'n/a'` strings as missing values by default (GH16471, GH16078)
- `pandas.HDFStore`'s string representation is now faster and less detailed. For the previous behavior, use `pandas.HDFStore.info()`. (GH16503).

- Compression defaults in HDF stores now follow pytables standards. Default is no compression and if `complib` is missing and `complevel` > 0 `zlib` is used (GH15943)
- `Index.get_indexer_non_unique()` now returns a ndarray indexer rather than an `Index`; this is consistent with `Index.get_indexer()` (GH16819)
- Removed the `@slow` decorator from `pandas._testing`, which caused issues for some downstream packages' test suites. Use `@pytest.mark.slow` instead, which achieves the same thing (GH16850)
- Moved definition of `MergeError` to the `pandas.errors` module.
- The signature of *Series.set_axis()* and *DataFrame.set_axis()* has been changed from `set_axis(axis, labels)` to `set_axis(labels, axis=0)`, for consistency with the rest of the API. The old signature is deprecated and will show a `FutureWarning` (GH14636)
- *Series.argmin()* and *Series.argmax()* will now raise a `TypeError` when used with `object` dtypes, instead of a `ValueError` (GH13595)
- *Period* is now immutable, and will now raise an `AttributeError` when a user tries to assign a new value to the `ordinal` or `freq` attributes (GH17116).
- *to_datetime()* when passed a tz-aware `origin=` kwarg will now raise a more informative `ValueError` rather than a `TypeError` (GH16842)
- *to_datetime()* now raises a `ValueError` when format includes `%W` or `%U` without also including day of the week and calendar year (GH16774)
- Renamed non-functional `index` to `index_col` in *read_stata()* to improve API consistency (GH16342)
- Bug in *DataFrame.drop()* caused boolean labels `False` and `True` to be treated as labels 0 and 1 respectively when dropping indices from a numeric index. This will now raise a ValueError (GH16877)
- Restricted DateOffset keyword arguments. Previously, `DateOffset` subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. (GH17176).

Deprecations

- `DataFrame.from_csv()` and `Series.from_csv()` have been deprecated in favor of *read_csv()* (GH4191)
- *read_excel()* has deprecated `sheetname` in favor of `sheet_name` for consistency with `.to_excel()` (GH10559).
- *read_excel()* has deprecated `parse_cols` in favor of `usecols` for consistency with *read_csv()* (GH4988)
- *read_csv()* has deprecated the `tupleize_cols` argument. Column tuples will always be converted to a `MultiIndex` (GH17060)
- *DataFrame.to_csv()* has deprecated the `tupleize_cols` argument. MultiIndex columns will be always written as rows in the CSV file (GH17060)
- The `convert` parameter has been deprecated in the `.take()` method, as it was not being respected (GH16948)
- `pd.options.html.border` has been deprecated in favor of `pd.options.display.html.border` (GH15793).
- `SeriesGroupBy.nth()` has deprecated `True` in favor of `'all'` for its kwarg `dropna` (GH11038).
- `DataFrame.as_blocks()` is deprecated, as this is exposing the internal implementation (GH17302)
- `pd.TimeGrouper` is deprecated in favor of *pandas.Grouper* (GH16747)

- `cdate_range` has been deprecated in favor of *`bdate_range()`*, which has gained `weekmask` and `holidays` parameters for building custom frequency date ranges. See the *documentation* for more details (GH17596)
- passing `categories` or `ordered` kwargs to *`Series.astype()`* is deprecated, in favor of passing a *CategoricalDtype* (GH17636)
- `.get_value` and `.set_value` on `Series`, `DataFrame`, `Panel`, `SparseSeries`, and `SparseDataFrame` are deprecated in favor of using `.iat[]` or `.at[]` accessors (GH15269)
- Passing a non-existent column in `.to_excel(..., columns=)` is deprecated and will raise a `KeyError` in the future (GH17295)
- `raise_on_error` parameter to *`Series.where()`*, *`Series.mask()`*, *`DataFrame.where()`*, *`DataFrame.mask()`* is deprecated, in favor of `errors=` (GH14968)
- Using *`DataFrame.rename_axis()`* and *`Series.rename_axis()`* to alter index or column *labels* is now deprecated in favor of using `.rename`. `rename_axis` may still be used to alter the name of the index or columns (GH17833).
- `reindex_axis()` has been deprecated in favor of *`reindex()`*. See *here* for more (GH17833).

Series.select and DataFrame.select

The `Series.select()` and `DataFrame.select()` methods are deprecated in favor of using `df.loc[labels.map(crit)]` (GH12401)

```
In [72]: df = pd.DataFrame({'A': [1, 2, 3]}, index=['foo', 'bar', 'baz'])
```

```
In [3]: df.select(lambda x: x in ['bar', 'baz'])
FutureWarning: select is deprecated and will be removed in a future release. You can␣
↪use .loc[crit] as a replacement
Out[3]:
     A
bar  2
baz  3
```

```
In [73]: df.loc[df.index.map(lambda x: x in ['bar', 'baz'])]
Out[73]:
     A
bar  2
baz  3

[2 rows x 1 columns]
```

Series.argmax and Series.argmin

The behavior of *`Series.argmax()`* and *`Series.argmin()`* have been deprecated in favor of *`Series.idxmax()`* and *`Series.idxmin()`*, respectively (GH16830).

For compatibility with NumPy arrays, `pd.Series` implements `argmax` and `argmin`. Since pandas 0.13.0, `argmax` has been an alias for *`pandas.Series.idxmax()`*, and `argmin` has been an alias for *`pandas.Series.idxmin()`*. They return the *label* of the maximum or minimum, rather than the *position*.

We've deprecated the current behavior of `Series.argmax` and `Series.argmin`. Using either of these will emit a `FutureWarning`. Use *`Series.idxmax()`* if you want the label of the maximum. Use `Series.values.`

argmax() if you want the position of the maximum. Likewise for the minimum. In a future release Series.argmax and Series.argmin will return the position of the maximum or minimum.

Removal of prior version deprecations/changes

- *read_excel()* has dropped the has_index_names parameter (GH10967)
- The pd.options.display.height configuration has been dropped (GH3663)
- The pd.options.display.line_width configuration has been dropped (GH2881)
- The pd.options.display.mpl_style configuration has been dropped (GH12190)
- Index has dropped the .sym_diff() method in favor of .symmetric_difference() (GH12591)
- Categorical has dropped the .order() and .sort() methods in favor of .sort_values() (GH12882)
- *eval()* and *DataFrame.eval()* have changed the default of inplace from None to False (GH11149)
- The function get_offset_name has been dropped in favor of the .freqstr attribute for an offset (GH11834)
- pandas no longer tests for compatibility with hdf5-files created with pandas < 0.11 (GH17404).

Performance improvements

- Improved performance of instantiating SparseDataFrame (GH16773)
- *Series.dt* no longer performs frequency inference, yielding a large speedup when accessing the attribute (GH17210)
- Improved performance of *set_categories()* by not materializing the values (GH17508)
- *Timestamp.microsecond* no longer re-computes on attribute access (GH17331)
- Improved performance of the *CategoricalIndex* for data that is already categorical dtype (GH17513)
- Improved performance of RangeIndex.min() and RangeIndex.max() by using RangeIndex properties to perform the computations (GH17607)

Documentation changes

- Several NaT method docstrings (e.g. NaT.ctime()) were incorrect (GH17327)
- The documentation has had references to versions < v0.17 removed and cleaned up (GH17442, GH17442, GH17404 & GH17504)

Bug fixes

Conversion

- Bug in assignment against datetime-like data with int may incorrectly convert to datetime-like (GH14145)
- Bug in assignment against int64 data with np.ndarray with float64 dtype may keep int64 dtype (GH14001)
- Fixed the return type of IntervalIndex.is_non_overlapping_monotonic to be a Python bool for consistency with similar attributes/methods. Previously returned a numpy.bool_. (GH17237)

- Bug in `IntervalIndex.is_non_overlapping_monotonic` when intervals are closed on both sides and overlap at a point (GH16560)
- Bug in *`Series.fillna()`* returns frame when `inplace=True` and `value` is dict (GH16156)
- Bug in `Timestamp.weekday_name` returning a UTC-based weekday name when localized to a timezone (GH17354)
- Bug in `Timestamp.replace` when replacing `tzinfo` around DST changes (GH15683)
- Bug in `Timedelta` construction and arithmetic that would not propagate the `Overflow` exception (GH17367)
- Bug in *`astype()`* converting to object dtype when passed extension type classes (`DatetimeTZDtype`, `CategoricalDtype`) rather than instances. Now a `TypeError` is raised when a class is passed (GH17780).
- Bug in *`to_numeric()`* in which elements were not always being coerced to numeric when `errors='coerce'` (GH17007, GH17125)
- Bug in `DataFrame` and `Series` constructors where `range` objects are converted to `int32` dtype on Windows instead of `int64` (GH16804)

Indexing

- When called with a null slice (e.g. `df.iloc[:]`), the `.iloc` and `.loc` indexers return a shallow copy of the original object. Previously they returned the original object. (GH13873).
- When called on an unsorted `MultiIndex`, the `loc` indexer now will raise `UnsortedIndexError` only if proper slicing is used on non-sorted levels (GH16734).
- Fixes regression in 0.20.3 when indexing with a string on a `TimedeltaIndex` (GH16896).
- Fixed `TimedeltaIndex.get_loc()` handling of `np.timedelta64` inputs (GH16909).
- Fix `MultiIndex.sort_index()` ordering when `ascending` argument is a list, but not all levels are specified, or are in a different order (GH16934).
- Fixes bug where indexing with `np.inf` caused an `OverflowError` to be raised (GH16957)
- Bug in reindexing on an empty `CategoricalIndex` (GH16770)
- Fixes `DataFrame.loc` for setting with alignment and tz-aware `DatetimeIndex` (GH16889)
- Avoids `IndexError` when passing an Index or Series to `.iloc` with older numpy (GH17193)
- Allow unicode empty strings as placeholders in multilevel columns in Python 2 (GH17099)
- Bug in `.iloc` when used with inplace addition or assignment and an int indexer on a `MultiIndex` causing the wrong indexes to be read from and written to (GH17148)
- Bug in `.isin()` in which checking membership in empty `Series` objects raised an error (GH16991)
- Bug in `CategoricalIndex` reindexing in which specified indices containing duplicates were not being respected (GH17323)
- Bug in intersection of `RangeIndex` with negative step (GH17296)
- Bug in `IntervalIndex` where performing a scalar lookup fails for included right endpoints of non-overlapping monotonic decreasing indexes (GH16417, GH17271)
- Bug in *`DataFrame.first_valid_index()`* and *`DataFrame.last_valid_index()`* when no valid entry (GH17400)
- Bug in *`Series.rename()`* when called with a callable, incorrectly alters the name of the `Series`, rather than the name of the `Index`. (GH17407)

- Bug in `String.str_get()` raises `IndexError` instead of inserting NaNs when using a negative index. (GH17704)

IO

- Bug in *`read_hdf()`* when reading a timezone aware index from `fixed` format HDFStore (GH17618)
- Bug in *`read_csv()`* in which columns were not being thoroughly de-duplicated (GH17060)
- Bug in *`read_csv()`* in which specified column names were not being thoroughly de-duplicated (GH17095)
- Bug in *`read_csv()`* in which non integer values for the header argument generated an unhelpful / unrelated error message (GH16338)
- Bug in *`read_csv()`* in which memory management issues in exception handling, under certain conditions, would cause the interpreter to segfault (GH14696, GH16798).
- Bug in *`read_csv()`* when called with `low_memory=False` in which a CSV with at least one column > 2GB in size would incorrectly raise a `MemoryError` (GH16798).
- Bug in *`read_csv()`* when called with a single-element list `header` would return a `DataFrame` of all NaN values (GH7757)
- Bug in *`DataFrame.to_csv()`* defaulting to 'ascii' encoding in Python 3, instead of 'utf-8' (GH17097)
- Bug in *`read_stata()`* where value labels could not be read when using an iterator (GH16923)
- Bug in *`read_stata()`* where the index was not set (GH16342)
- Bug in *`read_html()`* where import check fails when run in multiple threads (GH16928)
- Bug in *`read_csv()`* where automatic delimiter detection caused a `TypeError` to be thrown when a bad line was encountered rather than the correct error message (GH13374)
- Bug in *`DataFrame.to_html()`* with `notebook=True` where DataFrames with named indices or non-MultiIndex indices had undesired horizontal or vertical alignment for column or row labels, respectively (GH16792)
- Bug in *`DataFrame.to_html()`* in which there was no validation of the `justify` parameter (GH17527)
- Bug in *`HDFStore.select()`* when reading a contiguous mixed-data table featuring VLArray (GH17021)
- Bug in `to_json()` where several conditions (including objects with unprintable symbols, objects with deep recursion, overlong labels) caused segfaults instead of raising the appropriate exception (GH14256)

Plotting

- Bug in plotting methods using `secondary_y` and `fontsize` not setting secondary axis font size (GH12565)
- Bug when plotting `timedelta` and `datetime` dtypes on y-axis (GH16953)
- Line plots no longer assume monotonic x data when calculating xlims, they show the entire lines now even for unsorted x data. (GH11310, GH11471)
- With matplotlib 2.0.0 and above, calculation of x limits for line plots is left to matplotlib, so that its new default settings are applied. (GH15495)
- Bug in `Series.plot.bar` or `DataFrame.plot.bar` with `y` not respecting user-passed `color` (GH16822)
- Bug causing `plotting.parallel_coordinates` to reset the random seed when using random colors (GH17525)

GroupBy/resample/rolling

- Bug in `DataFrame.resample(...).size()` where an empty `DataFrame` did not return a `Series` (GH14962)
- Bug in *infer_freq()* causing indices with 2-day gaps during the working week to be wrongly inferred as business daily (GH16624)
- Bug in `.rolling(...).quantile()` which incorrectly used different defaults than *Series.quantile()* and *DataFrame.quantile()* (GH9413, GH16211)
- Bug in `groupby.transform()` that would coerce boolean dtypes back to float (GH16875)
- Bug in `Series.resample(...).apply()` where an empty `Series` modified the source index and did not return the name of a `Series` (GH14313)
- Bug in `.rolling(...).apply(...)` with a `DataFrame` with a `DatetimeIndex`, a `window` of a timedelta-convertible and `min_periods >= 1` (GH15305)
- Bug in `DataFrame.groupby` where index and column keys were not recognized correctly when the number of keys equaled the number of elements on the groupby axis (GH16859)
- Bug in `groupby.nunique()` with `TimeGrouper` which cannot handle `NaT` correctly (GH17575)
- Bug in `DataFrame.groupby` where a single level selection from a `MultiIndex` unexpectedly sorts (GH17537)
- Bug in `DataFrame.groupby` where spurious warning is raised when `Grouper` object is used to override ambiguous column name (GH17383)
- Bug in `TimeGrouper` differs when passes as a list and as a scalar (GH17530)

Sparse

- Bug in `SparseSeries` raises `AttributeError` when a dictionary is passed in as data (GH16905)
- Bug in `SparseDataFrame.fillna()` not filling all NaNs when frame was instantiated from SciPy sparse matrix (GH16112)
- Bug in `SparseSeries.unstack()` and `SparseDataFrame.stack()` (GH16614, GH15045)
- Bug in `make_sparse()` treating two numeric/boolean data, which have same bits, as same when array `dtype` is `object` (GH17574)
- `SparseArray.all()` and `SparseArray.any()` are now implemented to handle `SparseArray`, these were used but not implemented (GH17570)

Reshaping

- Joining/Merging with a non unique `PeriodIndex` raised a `TypeError` (GH16871)
- Bug in *crosstab()* where non-aligned series of integers were casted to float (GH17005)
- Bug in merging with categorical dtypes with datetimelikes incorrectly raised a `TypeError` (GH16900)
- Bug when using `isin()` on a large object series and large comparison array (GH16012)
- Fixes regression from 0.20, *Series.aggregate()* and *DataFrame.aggregate()* allow dictionaries as return values again (GH16741)

- Fixes dtype of result with integer dtype input, from *pivot_table()* when called with `margins=True` (GH17013)
- Bug in *crosstab()* where passing two `Series` with the same name raised a `KeyError` (GH13279)
- *Series.argmin()*, *Series.argmax()*, and their counterparts on `DataFrame` and groupby objects work correctly with floating point data that contains infinite values (GH13595).
- Bug in *unique()* where checking a tuple of strings raised a `TypeError` (GH17108)
- Bug in *concat()* where order of result index was unpredictable if it contained non-comparable elements (GH17344)
- Fixes regression when sorting by multiple columns on a `datetime64` dtype `Series` with `NaT` values (GH16836)
- Bug in *pivot_table()* where the result's columns did not preserve the categorical dtype of `columns` when `dropna` was `False` (GH17842)
- Bug in `DataFrame.drop_duplicates` where dropping with non-unique column names raised a `ValueError` (GH17836)
- Bug in `unstack()` which, when called on a list of levels, would discard the `fillna` argument (GH13971)
- Bug in the alignment of `range` objects and other list-likes with `DataFrame` leading to operations being performed row-wise instead of column-wise (GH17901)

Numeric

- Bug in `.clip()` with `axis=1` and a list-like for `threshold` is passed; previously this raised `ValueError` (GH15390)
- *Series.clip()* and *DataFrame.clip()* now treat NA values for upper and lower arguments as `None` instead of raising `ValueError` (GH17276).

Categorical

- Bug in *Series.isin()* when called with a categorical (GH16639)
- Bug in the categorical constructor with empty values and categories causing the `.categories` to be an empty `Float64Index` rather than an empty `Index` with object dtype (GH17248)
- Bug in categorical operations with *Series.cat* not preserving the original Series' name (GH17509)
- Bug in *DataFrame.merge()* failing for categorical columns with boolean/int data types (GH17187)
- Bug in constructing a `Categorical`/`CategoricalDtype` when the specified `categories` are of categorical type (GH17884).

PyPy

- Compatibility with PyPy in *read_csv()* with `usecols=[<unsorted ints>]` and *read_json()* (GH17351)
- Split tests into cases for CPython and PyPy where needed, which highlights the fragility of index matching with `float('nan')`, `np.nan` and `NAT` (GH17351)
- Fix *DataFrame.memory_usage()* to support PyPy. Objects on PyPy do not have a fixed size, so an approximation is used instead (GH17228)

Other

- Bug where some inplace operators were not being wrapped and produced a copy when invoked (GH12962)
- Bug in *eval()* where the `inplace` parameter was being incorrectly handled (GH16732)

Contributors

A total of 206 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- bpraggastis
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- cclauss +
- chernrick
- chris-b1
- dkamm +
- dwkenefick
- economy
- faic +
- fding253 +
- gfyoung

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- huashuai +
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- iulia +
- jaredsnyder
- jbrockmendel +
- jdeschenes
- jebob +
- jschendel +
- keitakurita
- kernc +
- kiwirob +
- kjford
- linebp
- lloydkirk
- louispotok +
- majiang +
- manikbhandari +
- matthiashuschle +
- mattip
- maxwasserman +
- mjlove12 +
- nmartensen +
- pandas-docs-bot +
- parchd-1 +
- philipphanemann +
- rdk1024 +
- reidy-p +
- ri938
- ruiann +
- rvernica +
- s-weigand +
- scotthavard92 +
- skwbc +
- step4me +

- tobycheese +
- topper-123 +
- tsdlovell
- ysau +
- zzgao +

5.9 Version 0.20

5.9.1 Version 0.20.3 (July 7, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

What's new in v0.20.3

- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *IO*
  - *Plotting*
  - *Reshaping*
  - *Categorical*
- *Contributors*

Bug fixes

- Fixed a bug in failing to compute rolling computations of a column-MultiIndexed `DataFrame` (GH16789, GH16825)
- Fixed a pytest marker failing downstream packages' tests suites (GH16680)

Conversion

- Bug in pickle compat prior to the v0.20.x series, when `UTC` is a timezone in a Series/DataFrame/Index (GH16608)
- Bug in `Series` construction when passing a `Series` with `dtype='category'` (GH16524).
- Bug in *`DataFrame.astype()`* when passing a `Series` as the `dtype` kwarg. (GH16717).

Indexing

- Bug in `Float64Index` causing an empty array instead of `None` to be returned from `.get(np.nan)` on a Series whose index did not contain any `NaN` s (GH8569)
- Bug in `MultiIndex.isin` causing an error when passing an empty iterable (GH16777)
- Fixed a bug in a slicing DataFrame/Series that have a `TimedeltaIndex` (GH16637)

IO

- Bug in *`read_csv()`* in which files weren't opened as binary files by the C engine on Windows, causing EOF characters mid-field, which would fail (GH16039, GH16559, GH16675)
- Bug in *`read_hdf()`* in which reading a `Series` saved to an HDF file in 'fixed' format fails when an explicit `mode='r'` argument is supplied (GH16583)
- Bug in *`DataFrame.to_latex()`* where `bold_rows` was wrongly specified to be `True` by default, whereas in reality row labels remained non-bold whatever parameter provided. (GH16707)
- Fixed an issue with *`DataFrame.style()`* where generated element ids were not unique (GH16780)
- Fixed loading a `DataFrame` with a `PeriodIndex`, from a `format='fixed'` HDFStore, in Python 3, that was written in Python 2 (GH16781)

Plotting

- Fixed regression that prevented RGB and RGBA tuples from being used as color arguments (GH16233)
- Fixed an issue with *`DataFrame.plot.scatter()`* that incorrectly raised a `KeyError` when categorical data is used for plotting (GH16199)

Reshaping

- `PeriodIndex` / `TimedeltaIndex.join` was missing the `sort=` kwarg (GH16541)
- Bug in joining on a `MultiIndex` with a `category` dtype for a level (GH16627).
- Bug in *`merge()`* when merging/joining with multiple categorical columns (GH16767)

Categorical

- Bug in `DataFrame.sort_values` not respecting the `kind` parameter with categorical data (GH16793)

Contributors

A total of 20 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Douglas Rudd
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5.9.2 Version 0.20.2 (June 4, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

What's new in v0.20.2

- *Enhancements*
- *Performance improvements*
- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *IO*
  - *Plotting*

  - *GroupBy/resample/rolling*
  - *Sparse*
  - *Reshaping*
  - *Numeric*
  - *Categorical*
  - *Other*
- *Contributors*

Enhancements

- Unblocked access to additional compression types supported in pytables: 'blosc:blosclz, 'blosc:lz4', 'blosc:lz4hc', 'blosc:snappy', 'blosc:zlib', 'blosc:zstd' (GH14478)
- `Series` provides a `to_latex` method (GH16180)
- A new groupby method *`ngroup()`*, parallel to the existing *`cumcount()`*, has been added to return the group order (GH11642); see *here*.

Performance improvements

- Performance regression fix when indexing with a list-like (GH16285)
- Performance regression fix for MultiIndexes (GH16319, GH16346)
- Improved performance of `.clip()` with scalar arguments (GH15400)
- Improved performance of groupby with categorical groupers (GH16413)
- Improved performance of `MultiIndex.remove_unused_levels()` (GH16556)

Bug fixes

- Silenced a warning on some Windows environments about "tput: terminal attributes: No such device or address" when detecting the terminal size. This fix only applies to python 3 (GH16496)
- Bug in using `pathlib.Path` or `py.path.local` objects with io functions (GH16291)
- Bug in `Index.symmetric_difference()` on two equal MultiIndex's, results in a `TypeError` (GH13490)
- Bug in `DataFrame.update()` with `overwrite=False` and `NaN values` (GH15593)
- Passing an invalid engine to *`read_csv()`* now raises an informative `ValueError` rather than `UnboundLocalError`. (GH16511)
- Bug in *`unique()`* on an array of tuples (GH16519)
- Bug in *`cut()`* when `labels` are set, resulting in incorrect label ordering (GH16459)
- Fixed a compatibility issue with IPython 6.0's tab completion showing deprecation warnings on `Categoricals` (GH16409)

Conversion

- Bug in *to_numeric()* in which empty data inputs were causing a segfault of the interpreter (GH16302)
- Silence numpy warnings when broadcasting DataFrame to Series with comparison ops (GH16378, GH16306)

Indexing

- Bug in DataFrame.reset_index(level=) with single level index (GH16263)
- Bug in partial string indexing with a monotonic, but not strictly-monotonic, index incorrectly reversing the slice bounds (GH16515)
- Bug in MultiIndex.remove_unused_levels() that would not return a MultiIndex equal to the original. (GH16556)

IO

- Bug in *read_csv()* when comment is passed in a space delimited text file (GH16472)
- Bug in *read_csv()* not raising an exception with nonexistent columns in usecols when it had the correct length (GH14671)
- Bug that would force importing of the clipboard routines unnecessarily, potentially causing an import error on startup (GH16288)
- Bug that raised IndexError when HTML-rendering an empty DataFrame (GH15953)
- Bug in *read_csv()* in which tarfile object inputs were raising an error in Python 2.x for the C engine (GH16530)
- Bug where DataFrame.to_html() ignored the index_names parameter (GH16493)
- Bug where pd.read_hdf() returns numpy strings for index names (GH13492)
- Bug in HDFStore.select_as_multiple() where start/stop arguments were not respected (GH16209)

Plotting

- Bug in DataFrame.plot with a single column and a list-like color (GH3486)
- Bug in plot where NaT in DatetimeIndex results in Timestamp.min (GH12405)
- Bug in DataFrame.boxplot where figsize keyword was not respected for non-grouped boxplots (GH11959)

GroupBy/resample/rolling

- Bug in creating a time-based rolling window on an empty `DataFrame` (GH15819)
- Bug in `rolling.cov()` with offset window (GH16058)
- Bug in `.resample()` and `.groupby()` when aggregating on integers (GH16361)

Sparse

- Bug in construction of `SparseDataFrame` from `scipy.sparse.dok_matrix` (GH16179)

Reshaping

- Bug in `DataFrame.stack` with unsorted levels in `MultiIndex` columns (GH16323)
- Bug in `pd.wide_to_long()` where no error was raised when `i` was not a unique identifier (GH16382)
- Bug in `Series.isin(..)` with a list of tuples (GH16394)
- Bug in construction of a `DataFrame` with mixed dtypes including an all-NaT column. (GH16395)
- Bug in `DataFrame.agg()` and `Series.agg()` with aggregating on non-callable attributes (GH16405)

Numeric

- Bug in `.interpolate()`, where `limit_direction` was not respected when `limit=None` (default) was passed (GH16282)

Categorical

- Fixed comparison operations considering the order of the categories when both categoricals are unordered (GH16014)

Other

- Bug in `DataFrame.drop()` with an empty-list with non-unique indices (GH16270)

Contributors

A total of 34 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.9.3 Version 0.20.1 (May 5, 2017)

This is a major release from 0.19.2 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- New `.agg()` API for Series/DataFrame similar to the groupby-rolling-resample API's, see *here*
- Integration with the `feather-format`, including a new top-level `pd.read_feather()` and `DataFrame.to_feather()` method, see *here*.

- The `.ix` indexer has been deprecated, see *here*
- `Panel` has been deprecated, see *here*
- Addition of an `IntervalIndex` and `Interval` scalar type, see *here*
- Improved user API when grouping by index levels in `.groupby()`, see *here*
- Improved support for `UInt64` dtypes, see *here*
- A new orient for JSON serialization, `orient='table'`, that uses the Table Schema spec and that gives the possibility for a more interactive repr in the Jupyter Notebook, see *here*
- Experimental support for exporting styled DataFrames (`DataFrame.style`) to Excel, see *here*
- Window binary corr/cov operations now return a MultiIndexed `DataFrame` rather than a `Panel`, as `Panel` is now deprecated, see *here*
- Support for S3 handling now uses `s3fs`, see *here*
- Google BigQuery support now uses the `pandas-gbq` library, see *here*

Warning: pandas has changed the internal structure and layout of the code base. This can affect imports that are not from the top-level `pandas.*` namespace, please see the changes *here*.

Check the *API Changes* and *deprecations* before updating.

Note: This is a combined release for 0.20.0 and 0.20.1. Version 0.20.1 contains one additional change for backwards-compatibility with downstream projects using pandas' `utils` routines. (GH16250)

What's new in v0.20.0

- *New features*
  - *Method `agg` API for DataFrame/Series*
  - *Keyword argument `dtype` for data IO*
  - *Method `.to_datetime()` has gained an `origin` parameter*
  - *GroupBy enhancements*
  - *Better support for compressed URLs in `read_csv`*
  - *Pickle file IO now supports compression*
  - *UInt64 support improved*
  - *GroupBy on categoricals*
  - *Table schema output*
  - *SciPy sparse matrix from/to SparseDataFrame*
  - *Excel output for styled DataFrames*
  - *IntervalIndex*
  - *Other enhancements*
- *Backwards incompatible API changes*

- *Possible incompatibility for HDF5 formats created with pandas < 0.13.0*
- *Map on Index types now return other Index types*
- *Accessing datetime fields of Index now return Index*
- *pd.unique will now be consistent with extension types*
- *S3 file handling*
- *Partial string indexing changes*
- *Concat of different float dtypes will not automatically upcast*
- *pandas Google BigQuery support has moved*
- *Memory usage for Index is more accurate*
- *DataFrame.sort_index changes*
- *GroupBy describe formatting*
- *Window binary corr/cov operations return a MultiIndex DataFrame*
- *HDFStore where string comparison*
- *Index.intersection and inner join now preserve the order of the left Index*
- *Pivot table always returns a DataFrame*
- *Other API changes*

- *Reorganization of the library: privacy changes*
  - *Modules privacy has changed*
  - `pandas.errors`
  - `pandas.testing`
  - `pandas.plotting`
  - *Other development changes*

- *Deprecations*
  - *Deprecate* `.ix`
  - *Deprecate Panel*
  - *Deprecate groupby.agg() with a dictionary when renaming*
  - *Deprecate .plotting*
  - *Other deprecations*

- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *IO*
  - *Plotting*

        - *GroupBy/resample/rolling*
        - *Sparse*
        - *Reshaping*
        - *Numeric*
        - *Other*
    - *Contributors*

New features

Method `agg` API for DataFrame/Series

Series & DataFrame have been enhanced to support the aggregation API. This is a familiar API from groupby, window operations, and resampling. This allows aggregation operations in a concise way by using *`agg()`* and *`transform()`*. The full documentation is *here* (GH1623).

Here is a sample

```
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
   ...:                   index=pd.date_range('1/1/2000', periods=10))
   ...:

In [2]: df.iloc[3:7] = np.nan

In [3]: df
Out[3]:
                   A         B         C
2000-01-01  0.469112 -0.282863 -1.509059
2000-01-02 -1.135632  1.212112 -0.173215
2000-01-03  0.119209 -1.044236 -0.861849
2000-01-04       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN
2000-01-08  0.113648 -1.478427  0.524988
2000-01-09  0.404705  0.577046 -1.715002
2000-01-10 -1.039268 -0.370647 -1.157892

[10 rows x 3 columns]
```

One can operate using string function names, callables, lists, or dictionaries of these.

Using a single function is equivalent to `.apply`.

```
In [4]: df.agg('sum')
Out[4]:
A   -1.068226
B   -1.387015
C   -4.892029
Length: 3, dtype: float64
```

Multiple aggregations with a list of functions.

```
In [5]: df.agg(['sum', 'min'])
Out[5]:
            A         B         C
sum -1.068226 -1.387015 -4.892029
min -1.135632 -1.478427 -1.715002

[2 rows x 3 columns]
```

Using a dict provides the ability to apply specific aggregations per column. You will get a matrix-like output of all of the aggregators. The output has one column per unique function. Those functions applied to a particular column will be `NaN`:

```
In [6]: df.agg({'A': ['sum', 'min'], 'B': ['min', 'max']})
Out[6]:
            A         B
sum -1.068226       NaN
min -1.135632 -1.478427
max       NaN  1.212112

[3 rows x 2 columns]
```

The API also supports a `.transform()` function for broadcasting results.

```
In [7]: df.transform(['abs', lambda x: x - x.min()])
Out[7]:
                   A                     B                     C
                 abs  <lambda>         abs  <lambda>         abs  <lambda>
2000-01-01  0.469112  1.604745  0.282863  1.195563  1.509059  0.205944
2000-01-02  1.135632  0.000000  1.212112  2.690539  0.173215  1.541787
2000-01-03  0.119209  1.254841  1.044236  0.434191  0.861849  0.853153
2000-01-04       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-05       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-06       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN       NaN       NaN       NaN
2000-01-08  0.113648  1.249281  1.478427  0.000000  0.524988  2.239990
2000-01-09  0.404705  1.540338  0.577046  2.055473  1.715002  0.000000
2000-01-10  1.039268  0.096364  0.370647  1.107780  1.157892  0.557110

[10 rows x 6 columns]
```

When presented with mixed dtypes that cannot be aggregated, `.agg()` will only take the valid aggregations. This is similar to how groupby `.agg()` works. (GH15015)

```
In [8]: df = pd.DataFrame({'A': [1, 2, 3],
   ...:                    'B': [1., 2., 3.],
   ...:                    'C': ['foo', 'bar', 'baz'],
   ...:                    'D': pd.date_range('20130101', periods=3)})
   ...:

In [9]: df.dtypes
Out[9]:
A             int64
B           float64
C            object
D    datetime64[ns]
Length: 4, dtype: object
```

```
In [10]: df.agg(['min', 'sum'])
Out[10]:
     A    B          C          D
min  1  1.0        bar 2013-01-01
sum  6  6.0  foobarbaz        NaT

[2 rows x 4 columns]
```

Keyword argument `dtype` for data IO

The `'python'` engine for *`read_csv()`*, as well as the *`read_fwf()`* function for parsing fixed-width text files and *`read_excel()`* for parsing Excel files, now accept the `dtype` keyword argument for specifying the types of specific columns (GH14295). See the *io docs* for more information.

```
In [11]: data = "a  b\n1  2\n3  4"

In [12]: pd.read_fwf(StringIO(data)).dtypes
Out[12]:
a    int64
b    int64
Length: 2, dtype: object

In [13]: pd.read_fwf(StringIO(data), dtype={'a': 'float64', 'b': 'object'}).dtypes
Out[13]:
a    float64
b     object
Length: 2, dtype: object
```

Method `.to_datetime()` has gained an `origin` parameter

`to_datetime()` has gained a new parameter, `origin`, to define a reference date from where to compute the resulting timestamps when parsing numerical values with a specific `unit` specified. (GH11276, GH11745)

For example, with 1960-01-01 as the starting date:

```
In [14]: pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
Out[14]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to `1970-01-01 00:00:00`, which is commonly called 'unix epoch' or POSIX time. This was the previous default, so this is a backward compatible change.

```
In [15]: pd.to_datetime([1, 2, 3], unit='D')
Out[15]: DatetimeIndex(['1970-01-02', '1970-01-03', '1970-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

GroupBy enhancements

Strings passed to `DataFrame.groupby()` as the `by` parameter may now reference either column names or index level names. Previously, only column names could be referenced. This allows to easily group by a column and index level at the same time. (GH5677)

```
In [16]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
   ....:           ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
   ....:

In [17]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])

In [18]: df = pd.DataFrame({'A': [1, 1, 1, 1, 2, 2, 3, 3],
   ....:                    'B': np.arange(8)},
   ....:                   index=index)
   ....:

In [19]: df
Out[19]:
              A  B
first second
bar   one     1  0
      two     1  1
baz   one     1  2
      two     1  3
foo   one     2  4
      two     2  5
qux   one     3  6
      two     3  7

[8 rows x 2 columns]

In [20]: df.groupby(['second', 'A']).sum()
Out[20]:
           B
second A
one    1   2
       2   4
       3   6
two    1   4
       2   5
       3   7

[6 rows x 1 columns]
```

Better support for compressed URLs in `read_csv`

The compression code was refactored (GH12688). As a result, reading dataframes from URLs in *`read_csv()`* or *`read_table()`* now supports additional compression methods: `xz`, `bz2`, and `zip` (GH14570). Previously, only `gzip` compression was supported. By default, compression of URLs and paths are now inferred using their file extensions. Additionally, support for bz2 compression in the python 2 C-engine improved (GH14874).

```
In [21]: url = ('https://github.com/{repo}/raw/{branch}/{path}'
   ....:        .format(repo='pandas-dev/pandas',
   ....:                branch='master',
```

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```
   ....:                 path='pandas/tests/io/parser/data/salaries.csv.bz2'))
   ....:

# default, infer compression
In [22]: df = pd.read_csv(url, sep='\t', compression='infer')

# explicitly specify compression
In [23]: df = pd.read_csv(url, sep='\t', compression='bz2')

In [24]: df.head(2)
Out[24]:
       S  X  E  M
0  13876  1  1  1
1  11608  1  3  0

[2 rows x 4 columns]
```

Pickle file IO now supports compression

read_pickle(), *DataFrame.to_pickle()* and *Series.to_pickle()* can now read from and write to compressed pickle files. Compression methods can be an explicit parameter or be inferred from the file extension. See *the docs here.*

```
In [25]: df = pd.DataFrame({'A': np.random.randn(1000),
   ....:                    'B': 'foo',
   ....:                    'C': pd.date_range('20130101', periods=1000, freq='s')})
   ....:
```

Using an explicit compression type

```
In [26]: df.to_pickle("data.pkl.compress", compression="gzip")

In [27]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")

In [28]: rt.head()
Out[28]:
          A    B                   C
0 -1.344312  foo 2013-01-01 00:00:00
1  0.844885  foo 2013-01-01 00:00:01
2  1.075770  foo 2013-01-01 00:00:02
3 -0.109050  foo 2013-01-01 00:00:03
4  1.643563  foo 2013-01-01 00:00:04

[5 rows x 3 columns]
```

The default is to infer the compression type from the extension (`compression='infer'`):

```
In [29]: df.to_pickle("data.pkl.gz")

In [30]: rt = pd.read_pickle("data.pkl.gz")

In [31]: rt.head()
Out[31]:
          A    B                   C
0 -1.344312  foo 2013-01-01 00:00:00
```

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```
1  0.844885  foo 2013-01-01 00:00:01
2  1.075770  foo 2013-01-01 00:00:02
3 -0.109050  foo 2013-01-01 00:00:03
4  1.643563  foo 2013-01-01 00:00:04

[5 rows x 3 columns]

In [32]: df["A"].to_pickle("s1.pkl.bz2")

In [33]: rt = pd.read_pickle("s1.pkl.bz2")

In [34]: rt.head()
Out[34]:
0   -1.344312
1    0.844885
2    1.075770
3   -0.109050
4    1.643563
Name: A, Length: 5, dtype: float64
```

UInt64 support improved

pandas has significantly improved support for operations involving unsigned, or purely non-negative, integers. Previously, handling these integers would result in improper rounding or data-type casting, leading to incorrect results. Notably, a new numerical index, `UInt64Index`, has been created (GH14937)

```
In [35]: idx = pd.UInt64Index([1, 2, 3])

In [36]: df = pd.DataFrame({'A': ['a', 'b', 'c']}, index=idx)

In [37]: df.index
Out[37]: UInt64Index([1, 2, 3], dtype='uint64')
```

- Bug in converting object elements of array-like objects to unsigned 64-bit integers (GH4471, GH14982)
- Bug in `Series.unique()` in which unsigned 64-bit integers were causing overflow (GH14721)
- Bug in `DataFrame` construction in which unsigned 64-bit integer elements were being converted to objects (GH14881)
- Bug in `pd.read_csv()` in which unsigned 64-bit integer elements were being improperly converted to the wrong data types (GH14983)
- Bug in `pd.unique()` in which unsigned 64-bit integers were causing overflow (GH14915)
- Bug in `pd.value_counts()` in which unsigned 64-bit integers were being erroneously truncated in the output (GH14934)

GroupBy on categoricals

In previous versions, `.groupby(..., sort=False)` would fail with a `ValueError` when grouping on a categorical series with some categories not appearing in the data. (GH13179)

```
In [38]: chromosomes = np.r_[np.arange(1, 23).astype(str), ['X', 'Y']]

In [39]: df = pd.DataFrame({
   ....:     'A': np.random.randint(100),
   ....:     'B': np.random.randint(100),
   ....:     'C': np.random.randint(100),
   ....:     'chromosomes': pd.Categorical(np.random.choice(chromosomes, 100),
   ....:                                   categories=chromosomes,
   ....:                                   ordered=True)})
   ....:

In [40]: df
Out[40]:
     A   B   C chromosomes
0   87  22  81           4
1   87  22  81          13
2   87  22  81          22
3   87  22  81           2
4   87  22  81           6
..  ..  ..  ..         ...
95  87  22  81           8
96  87  22  81          11
97  87  22  81           X
98  87  22  81           1
99  87  22  81          19

[100 rows x 4 columns]
```

Previous behavior:

```
In [3]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
---------------------------------------------------------------------------
ValueError: items in new_categories are not the same as in old categories
```

New behavior:

```
In [41]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
Out[41]:
                A    B    C
chromosomes
2             348   88  324
3             348   88  324
4             348   88  324
5             261   66  243
6             174   44  162
...           ...  ...  ...
22            348   88  324
X             348   88  324
Y             435  110  405
1               0    0    0
21              0    0    0

[24 rows x 3 columns]
```

Table schema output

The new orient `'table'` for *`DataFrame.to_json()`* will generate a Table Schema compatible string representation of the data.

```
In [42]: df = pd.DataFrame(
   ....:     {'A': [1, 2, 3],
   ....:      'B': ['a', 'b', 'c'],
   ....:      'C': pd.date_range('2016-01-01', freq='d', periods=3)},
   ....:     index=pd.Index(range(3), name='idx'))
   ....:

In [43]: df
Out[43]:
     A  B          C
idx
0    1  a 2016-01-01
1    2  b 2016-01-02
2    3  c 2016-01-03

[3 rows x 3 columns]

In [44]: df.to_json(orient='table')
Out[44]: '{"schema":{"fields":[{"name":"idx","type":"integer"},{"name":"A","type":
↪"integer"},{"name":"B","type":"string"},{"name":"C","type":"datetime"}],"primaryKey
↪":["idx"],"pandas_version":"0.20.0"},"data":[{"idx":0,"A":1,"B":"a","C":"2016-01-
↪01T00:00:00.000Z"},{"idx":1,"A":2,"B":"b","C":"2016-01-02T00:00:00.000Z"},{"idx":2,
↪"A":3,"B":"c","C":"2016-01-03T00:00:00.000Z"}]}'
```

See *IO: Table Schema for more information*.

Additionally, the repr for `DataFrame` and `Series` can now publish this JSON Table schema representation of the Series or DataFrame if you are using IPython (or another frontend like nteract using the Jupyter messaging protocol). This gives frontends like the Jupyter notebook and nteract more flexibility in how they display pandas objects, since they have more information about the data. You must enable this by setting the `display.html.table_schema` option to `True`.

SciPy sparse matrix from/to SparseDataFrame

pandas now supports creating sparse dataframes directly from `scipy.sparse.spmatrix` instances. See the *documentation* for more information. (GH4343)

All sparse formats are supported, but matrices that are not in `COOrdinate` format will be converted, copying data as needed.

```
from scipy.sparse import csr_matrix
arr = np.random.random(size=(1000, 5))
arr[arr < .9] = 0
sp_arr = csr_matrix(arr)
sp_arr
sdf = pd.SparseDataFrame(sp_arr)
sdf
```

To convert a `SparseDataFrame` back to sparse SciPy matrix in COO format, you can use:

```
sdf.to_coo()
```

Excel output for styled DataFrames

Experimental support has been added to export `DataFrame.style` formats to Excel using the `openpyxl` engine. (GH15530)

For example, after running the following, `styled.xlsx` renders as below:

```
In [45]: np.random.seed(24)

In [46]: df = pd.DataFrame({'A': np.linspace(1, 10, 10)})

In [47]: df = pd.concat([df, pd.DataFrame(np.random.RandomState(24).randn(10, 4),
   ....:                                  columns=list('BCDE'))],
   ....:                 axis=1)
   ....:

In [48]: df.iloc[0, 2] = np.nan

In [49]: df
Out[49]:
      A         B         C         D         E
0   1.0  1.329212       NaN -0.316280 -0.990810
1   2.0 -1.070816 -1.438713  0.564417  0.295722
2   3.0 -1.626404  0.219565  0.678805  1.889273
3   4.0  0.961538  0.104011 -0.481165  0.850229
4   5.0  1.453425  1.057737  0.165562  0.515018
5   6.0 -1.336936  0.562861  1.392855 -0.063328
6   7.0  0.121668  1.207603 -0.002040  1.627796
7   8.0  0.354493  1.037528 -0.385684  0.519818
8   9.0  1.686583 -1.325963  1.428984 -2.089354
9  10.0 -0.129820  0.631523 -0.586538  0.290720

[10 rows x 5 columns]

In [50]: styled = (df.style
   ....:           .applymap(lambda val: 'color: %s' % 'red' if val < 0 else 'black')
   ....:           .highlight_max())
   ....:

In [51]: styled.to_excel('styled.xlsx', engine='openpyxl')
```

	A	B	C	D	E	F
1		A	B	C	D	E
2	0	1	1.329212		-0.31628	-0.99081
3	1	2	-1.070816	-1.438713	0.564417	0.295722
4	2	3	-1.626404	0.219565	0.678805	1.889273
5	3	4	0.961538	0.104011	-0.481165	0.850229
6	4	5	1.453425	1.057737	0.165562	0.515018
7	5	6	-1.336936	0.562861	1.392855	-0.063328
8	6	7	0.121668	1.207603	-0.00204	1.627796
9	7	8	0.354493	1.037528	-0.385684	0.519818
10	8	9	1.686583	-1.325963	1.428984	-2.089354
11	9	10	-0.12982	0.631523	-0.586538	0.29072

See the *Style documentation* for more detail.

IntervalIndex

pandas has gained an `IntervalIndex` with its own dtype, `interval` as well as the `Interval` scalar type. These allow first-class support for interval notation, specifically as a return type for the categories in `cut()` and `qcut()`. The `IntervalIndex` allows some unique indexing, see the *docs*. (GH7640, GH8625)

Warning: These indexing behaviors of the IntervalIndex are provisional and may change in a future version of pandas. Feedback on usage is welcome.

Previous behavior:

The returned categories were strings, representing Intervals

```
In [1]: c = pd.cut(range(4), bins=2)

In [2]: c
Out[2]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3], (1.5, 3]]
Categories (2, object): [(-0.003, 1.5] < (1.5, 3]]

In [3]: c.categories
Out[3]: Index(['(-0.003, 1.5]', '(1.5, 3]'], dtype='object')
```

New behavior:

```
In [52]: c = pd.cut(range(4), bins=2)

In [53]: c
Out[53]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3.0], (1.5, 3.0]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]

In [54]: c.categories
Out[54]:
IntervalIndex([(-0.003, 1.5], (1.5, 3.0]],
              closed='right',
              dtype='interval[float64]')
```

Furthermore, this allows one to bin *other* data with these same bins, with `NaN` representing a missing value similar to other dtypes.

```
In [55]: pd.cut([0, 3, 5, 1], bins=c.categories)
Out[55]:
[(-0.003, 1.5], (1.5, 3.0], NaN, (-0.003, 1.5]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]
```

An `IntervalIndex` can also be used in `Series` and `DataFrame` as the index.

```
In [56]: df = pd.DataFrame({'A': range(4),
   ....:                    'B': pd.cut([0, 3, 1, 1], bins=c.categories)
   ....:                    }).set_index('B')
   ....:
```

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```
In [57]: df
Out[57]:
                A
B
(-0.003, 1.5]   0
(1.5, 3.0]      1
(-0.003, 1.5]   2
(-0.003, 1.5]   3

[4 rows x 1 columns]
```

Selecting via a specific interval:

```
In [58]: df.loc[pd.Interval(1.5, 3.0)]
Out[58]:
A    1
Name: (1.5, 3.0], Length: 1, dtype: int64
```

Selecting via a scalar value that is contained *in* the intervals.

```
In [59]: df.loc[0]
Out[59]:
                A
B
(-0.003, 1.5]   0
(-0.003, 1.5]   2
(-0.003, 1.5]   3

[3 rows x 1 columns]
```

Other enhancements

- `DataFrame.rolling()` now accepts the parameter `closed='right'|'left'|'both'|'neither'` to choose the rolling window-endpoint closedness. See the *documentation* (GH13965)
- Integration with the `feather-format`, including a new top-level `pd.read_feather()` and `DataFrame.to_feather()` method, see *here*.
- `Series.str.replace()` now accepts a callable, as replacement, which is passed to `re.sub` (GH15055)
- `Series.str.replace()` now accepts a compiled regular expression as a pattern (GH15446)
- `Series.sort_index` accepts parameters `kind` and `na_position` (GH13589, GH14444)
- `DataFrame` and `DataFrame.groupby()` have gained a `nunique()` method to count the distinct values over an axis (GH14336, GH15197).
- `DataFrame` has gained a `melt()` method, equivalent to `pd.melt()`, for unpivoting from a wide to long format (GH12640).
- `pd.read_excel()` now preserves sheet order when using `sheetname=None` (GH9930)
- Multiple offset aliases with decimal points are now supported (e.g. `0.5min` is parsed as `30s`) (GH8419)
- `.isnull()` and `.notnull()` have been added to `Index` object to make them more consistent with the `Series` API (GH15300)

- New `UnsortedIndexError` (subclass of `KeyError`) raised when indexing/slicing into an unsorted MultiIndex (GH11897). This allows differentiation between errors due to lack of sorting or an incorrect key. See *here*
- `MultiIndex` has gained a `.to_frame()` method to convert to a `DataFrame` (GH12397)
- `pd.cut` and `pd.qcut` now support datetime64 and timedelta64 dtypes (GH14714, GH14798)
- `pd.qcut` has gained the `duplicates='raise'|'drop'` option to control whether to raise on duplicated edges (GH7751)
- `Series` provides a `to_excel` method to output Excel files (GH8825)
- The `usecols` argument in `pd.read_csv()` now accepts a callable function as a value (GH14154)
- The `skiprows` argument in `pd.read_csv()` now accepts a callable function as a value (GH10882)
- The `nrows` and `chunksize` arguments in `pd.read_csv()` are supported if both are passed (GH6774, GH15755)
- `DataFrame.plot` now prints a title above each subplot if `suplots=True` and `title` is a list of strings (GH14753)
- `DataFrame.plot` can pass the matplotlib 2.0 default color cycle as a single string as color parameter, see here. (GH15516)
- `Series.interpolate()` now supports timedelta as an index type with `method='time'` (GH6424)
- Addition of a `level` keyword to `DataFrame/Series.rename` to rename labels in the specified level of a MultiIndex (GH4160).
- `DataFrame.reset_index()` will now interpret a tuple `index.name` as a key spanning across levels of `columns`, if this is a `MultiIndex` (GH16164)
- `Timedelta.isoformat` method added for formatting Timedeltas as an ISO 8601 duration. See the *Timedelta docs* (GH15136)
- `.select_dtypes()` now allows the string `datetimetz` to generically select datetimes with tz (GH14910)
- The `.to_latex()` method will now accept `multicolumn` and `multirow` arguments to use the accompanying LaTeX enhancements
- `pd.merge_asof()` gained the option `direction='backward'|'forward'|'nearest'` (GH14887)
- `Series/DataFrame.asfreq()` have gained a `fill_value` parameter, to fill missing values (GH3715).
- `Series/DataFrame.resample.asfreq` have gained a `fill_value` parameter, to fill missing values during resampling (GH3715).
- *`pandas.util.hash_pandas_object()`* has gained the ability to hash a `MultiIndex` (GH15224)
- `Series/DataFrame.squeeze()` have gained the `axis` parameter. (GH15339)
- `DataFrame.to_excel()` has a new `freeze_panes` parameter to turn on Freeze Panes when exporting to Excel (GH15160)
- `pd.read_html()` will parse multiple header rows, creating a MultiIndex header. (GH13434).
- HTML table output skips `colspan` or `rowspan` attribute if equal to 1. (GH15403)
- *`pandas.io.formats.style.Styler`* template now has blocks for easier extension, see the *example notebook* (GH15649)
- *`Styler.render()`* now accepts `**kwargs` to allow user-defined variables in the template (GH15649)

- Compatibility with Jupyter notebook 5.0; MultiIndex column labels are left-aligned and MultiIndex row-labels are top-aligned (GH15379)
- `TimedeltaIndex` now has a custom date-tick formatter specifically designed for nanosecond level precision (GH8711)
- `pd.api.types.union_categoricals` gained the `ignore_ordered` argument to allow ignoring the ordered attribute of unioned categoricals (GH13410). See the *categorical union docs* for more information.
- `DataFrame.to_latex()` and `DataFrame.to_string()` now allow optional header aliases. (GH15536)
- Re-enable the `parse_dates` keyword of `pd.read_excel()` to parse string columns as dates (GH14326)
- Added `.empty` property to subclasses of `Index`. (GH15270)
- Enabled floor division for `Timedelta` and `TimedeltaIndex` (GH15828)
- `pandas.io.json.json_normalize()` gained the option `errors='ignore'|'raise'`; the default is `errors='raise'` which is backward compatible. (GH14583)
- `pandas.io.json.json_normalize()` with an empty `list` will return an empty `DataFrame` (GH15534)
- `pandas.io.json.json_normalize()` has gained a `sep` option that accepts `str` to separate joined fields; the default is ".", which is backward compatible. (GH14883)
- *`MultiIndex.remove_unused_levels()`* has been added to facilitate *removing unused levels*. (GH15694)
- `pd.read_csv()` will now raise a `ParserError` error whenever any parsing error occurs (GH15913, GH15925)
- `pd.read_csv()` now supports the `error_bad_lines` and `warn_bad_lines` arguments for the Python parser (GH15925)
- The `display.show_dimensions` option can now also be used to specify whether the length of a `Series` should be shown in its repr (GH7117).
- `parallel_coordinates()` has gained a `sort_labels` keyword argument that sorts class labels and the colors assigned to them (GH15908)
- Options added to allow one to turn on/off using `bottleneck` and `numexpr`, see *here* (GH16157)
- `DataFrame.style.bar()` now accepts two more options to further customize the bar chart. Bar alignment is set with `align='left'|'mid'|'zero'`, the default is "left", which is backward compatible; You can now pass a list of `color=[color_negative, color_positive]`. (GH14757)

Backwards incompatible API changes

Possible incompatibility for HDF5 formats created with pandas < 0.13.0

`pd.TimeSeries` was deprecated officially in 0.17.0, though has already been an alias since 0.13.0. It has been dropped in favor of `pd.Series`. (GH15098).

This *may* cause HDF5 files that were created in prior versions to become unreadable if `pd.TimeSeries` was used. This is most likely to be for pandas < 0.13.0. If you find yourself in this situation. You can use a recent prior version of pandas to read in your HDF5 files, then write them out again after applying the procedure below.

```
In [2]: s = pd.TimeSeries([1, 2, 3], index=pd.date_range('20130101', periods=3))

In [3]: s
Out[3]:
2013-01-01    1
2013-01-02    2
2013-01-03    3
Freq: D, dtype: int64

In [4]: type(s)
Out[4]: pandas.core.series.TimeSeries

In [5]: s = pd.Series(s)

In [6]: s
Out[6]:
2013-01-01    1
2013-01-02    2
2013-01-03    3
Freq: D, dtype: int64

In [7]: type(s)
Out[7]: pandas.core.series.Series
```

Map on Index types now return other Index types

`map` on an `Index` now returns an `Index`, not a numpy array (GH12766)

```
In [60]: idx = pd.Index([1, 2])

In [61]: idx
Out[61]: Int64Index([1, 2], dtype='int64')

In [62]: mi = pd.MultiIndex.from_tuples([(1, 2), (2, 4)])

In [63]: mi
Out[63]:
MultiIndex([(1, 2),
            (2, 4)],
           )
```

Previous behavior:

```
In [5]: idx.map(lambda x: x * 2)
Out[5]: array([2, 4])

In [6]: idx.map(lambda x: (x, x * 2))
Out[6]: array([(1, 2), (2, 4)], dtype=object)

In [7]: mi.map(lambda x: x)
Out[7]: array([(1, 2), (2, 4)], dtype=object)

In [8]: mi.map(lambda x: x[0])
Out[8]: array([1, 2])
```

New behavior:

```
In [64]: idx.map(lambda x: x * 2)
Out[64]: Int64Index([2, 4], dtype='int64')

In [65]: idx.map(lambda x: (x, x * 2))
Out[65]:
MultiIndex([(1, 2),
            (2, 4)],
           )

In [66]: mi.map(lambda x: x)
Out[66]:
MultiIndex([(1, 2),
            (2, 4)],
           )

In [67]: mi.map(lambda x: x[0])
Out[67]: Int64Index([1, 2], dtype='int64')
```

`map` on a `Series` with `datetime64` values may return `int64` dtypes rather than `int32`

```
In [68]: s = pd.Series(pd.date_range('2011-01-02T00:00', '2011-01-02T02:00', freq='H')
   ....:                .tz_localize('Asia/Tokyo'))
   ....:

In [69]: s
Out[69]:
0   2011-01-02 00:00:00+09:00
1   2011-01-02 01:00:00+09:00
2   2011-01-02 02:00:00+09:00
Length: 3, dtype: datetime64[ns, Asia/Tokyo]
```

Previous behavior:

```
In [9]: s.map(lambda x: x.hour)
Out[9]:
0    0
1    1
2    2
dtype: int32
```

New behavior:

```
In [70]: s.map(lambda x: x.hour)
Out[70]:
0    0
1    1
2    2
Length: 3, dtype: int64
```

Accessing datetime fields of Index now return Index

The datetime-related attributes (see *here* for an overview) of `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex` previously returned numpy arrays. They will now return a new `Index` object, except in the case of a boolean field, where the result will still be a boolean ndarray. (GH15022)

Previous behaviour:

```
In [1]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')

In [2]: idx.hour
Out[2]: array([ 0, 10, 20,  6, 16], dtype=int32)
```

New behavior:

```
In [71]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')

In [72]: idx.hour
Out[72]: Int64Index([0, 10, 20, 6, 16], dtype='int64')
```

This has the advantage that specific `Index` methods are still available on the result. On the other hand, this might have backward incompatibilities: e.g. compared to numpy arrays, `Index` objects are not mutable. To get the original ndarray, you can always convert explicitly using `np.asarray(idx.hour)`.

pd.unique will now be consistent with extension types

In prior versions, using *`Series.unique()`* and *`pandas.unique()`* on `Categorical` and tz-aware data-types would yield different return types. These are now made consistent. (GH15903)

- Datetime tz-aware

  Previous behaviour:

```
# Series
In [5]: pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
   ...:            pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[5]: array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],␣
↪dtype=object)

In [6]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
   ...:                      pd.Timestamp('20160101', tz='US/Eastern')]))
Out[6]: array(['2016-01-01T05:00:00.000000000'], dtype='datetime64[ns]')

# Index
In [7]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
   ...:           pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[7]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/
↪Eastern]', freq=None)

In [8]: pd.unique([pd.Timestamp('20160101', tz='US/Eastern'),
   ...:            pd.Timestamp('20160101', tz='US/Eastern')])
Out[8]: array(['2016-01-01T05:00:00.000000000'], dtype='datetime64[ns]')
```

  New behavior:

```
# Series, returns an array of Timestamp tz-aware
In [73]: pd.Series([pd.Timestamp(r'20160101', tz=r'US/Eastern'),
   ....:            pd.Timestamp(r'20160101', tz=r'US/Eastern')]).unique()
   ....:
Out[73]:
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]

In [74]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
   ....:           pd.Timestamp('20160101', tz='US/Eastern')]))
   ....:
Out[74]:
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]

# Index, returns a DatetimeIndex
In [75]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
   ....:           pd.Timestamp('20160101', tz='US/Eastern')]).unique()
   ....:
Out[75]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/
↪Eastern]', freq=None)

In [76]: pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
   ....:                     pd.Timestamp('20160101', tz='US/Eastern')]))
   ....:
Out[76]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/
↪Eastern]', freq=None)
```

- Categoricals

  Previous behaviour:

```
In [1]: pd.Series(list('baabc'), dtype='category').unique()
Out[1]:
[b, a, c]
Categories (3, object): [b, a, c]

In [2]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[2]: array(['b', 'a', 'c'], dtype=object)
```

  New behavior:

```
# returns a Categorical
In [77]: pd.Series(list('baabc'), dtype='category').unique()
Out[77]:
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']

In [78]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[78]:
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```

S3 file handling

pandas now uses s3fs for handling S3 connections. This shouldn't break any code. However, since `s3fs` is not a required dependency, you will need to install it separately, like `boto` in prior versions of pandas. (GH11915).

Partial string indexing changes

DatetimeIndex Partial String Indexing now works as an exact match, provided that string resolution coincides with index resolution, including a case when both are seconds (GH14826). See *Slice vs. Exact Match* for details.

```
In [79]: df = pd.DataFrame({'a': [1, 2, 3]}, pd.DatetimeIndex(['2011-12-31 23:59:59',
   ....:                                                       '2012-01-01 00:00:00',
   ....:                                                       '2012-01-01 00:00:01
↪'']))
   ....:
```

Previous behavior:

```
In [4]: df['2011-12-31 23:59:59']
Out[4]:
                     a
2011-12-31 23:59:59  1

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]:
2011-12-31 23:59:59    1
Name: a, dtype: int64
```

New behavior:

```
In [4]: df['2011-12-31 23:59:59']
KeyError: '2011-12-31 23:59:59'

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]: 1
```

Concat of different float dtypes will not automatically upcast

Previously, `concat` of multiple objects with different `float` dtypes would automatically upcast results to a dtype of `float64`. Now the smallest acceptable dtype will be used (GH13247)

```
In [80]: df1 = pd.DataFrame(np.array([1.0], dtype=np.float32, ndmin=2))

In [81]: df1.dtypes
Out[81]:
0    float32
Length: 1, dtype: object

In [82]: df2 = pd.DataFrame(np.array([np.nan], dtype=np.float32, ndmin=2))

In [83]: df2.dtypes
Out[83]:
0    float32
Length: 1, dtype: object
```

Previous behavior:

```
In [7]: pd.concat([df1, df2]).dtypes
Out[7]:
0    float64
dtype: object
```

New behavior:

```
In [84]: pd.concat([df1, df2]).dtypes
Out[84]:
0    float32
Length: 1, dtype: object
```

pandas Google BigQuery support has moved

pandas has split off Google BigQuery support into a separate package `pandas-gbq`. You can `conda install pandas-gbq -c conda-forge` or `pip install pandas-gbq` to get it. The functionality of *`read_gbq()`* and *`DataFrame.to_gbq()`* remain the same with the currently released version of `pandas-gbq=0.1.4`. Documentation is now hosted here (GH15347)

Memory usage for Index is more accurate

In previous versions, showing `.memory_usage()` on a pandas structure that has an index, would only include actual index values and not include structures that facilitated fast indexing. This will generally be different for `Index` and `MultiIndex` and less-so for other index types. (GH15237)

Previous behavior:

```
In [8]: index = pd.Index(['foo', 'bar', 'baz'])

In [9]: index.memory_usage(deep=True)
Out[9]: 180

In [10]: index.get_loc('foo')
Out[10]: 0

In [11]: index.memory_usage(deep=True)
Out[11]: 180
```

New behavior:

```
In [8]: index = pd.Index(['foo', 'bar', 'baz'])

In [9]: index.memory_usage(deep=True)
Out[9]: 180

In [10]: index.get_loc('foo')
Out[10]: 0

In [11]: index.memory_usage(deep=True)
Out[11]: 260
```

DataFrame.sort_index changes

In certain cases, calling `.sort_index()` on a MultiIndexed DataFrame would return the *same* DataFrame without seeming to sort. This would happen with a `lexsorted`, but non-monotonic levels. (GH15622, GH15687, GH14015, GH13431, GH15797)

This is *unchanged* from prior versions, but shown for illustration purposes:

```
In [85]: df = pd.DataFrame(np.arange(6), columns=['value'],
   ....:                   index=pd.MultiIndex.from_product([list('BA'), range(3)]))
   ....:

In [86]: df
Out[86]:
     value
B 0      0
  1      1
  2      2
A 0      3
  1      4
  2      5

[6 rows x 1 columns]
```

```
In [87]: df.index.is_lexsorted()
Out[87]: False

In [88]: df.index.is_monotonic
Out[88]: False
```

Sorting works as expected

```
In [89]: df.sort_index()
Out[89]:
     value
A 0      3
  1      4
  2      5
B 0      0
  1      1
  2      2

[6 rows x 1 columns]
```

```
In [90]: df.sort_index().index.is_lexsorted()
Out[90]: True

In [91]: df.sort_index().index.is_monotonic
Out[91]: True
```

However, this example, which has a non-monotonic 2nd level, doesn't behave as desired.

```
In [92]: df = pd.DataFrame({'value': [1, 2, 3, 4]},
   ....:                   index=pd.MultiIndex([['a', 'b'], ['bb', 'aa']],
   ....:                                       [[0, 0, 1, 1], [0, 1, 0, 1]]))
   ....:
```

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```
In [93]: df
Out[93]:
      value
a bb      1
  aa      2
b bb      3
  aa      4

[4 rows x 1 columns]
```

Previous behavior:

```
In [11]: df.sort_index()
Out[11]:
      value
a bb      1
  aa      2
b bb      3
  aa      4

In [14]: df.sort_index().index.is_lexsorted()
Out[14]: True

In [15]: df.sort_index().index.is_monotonic
Out[15]: False
```

New behavior:

```
In [94]: df.sort_index()
Out[94]:
      value
a aa      2
  bb      1
b aa      4
  bb      3

[4 rows x 1 columns]

In [95]: df.sort_index().index.is_lexsorted()
Out[95]: True

In [96]: df.sort_index().index.is_monotonic
Out[96]: True
```

GroupBy describe formatting

The output formatting of `groupby.describe()` now labels the `describe()` metrics in the columns instead of the index. This format is consistent with `groupby.agg()` when applying multiple functions at once. (GH4792)

Previous behavior:

```
In [1]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})

In [2]: df.groupby('A').describe()
Out[2]:
```

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```
                B
A
1 count  2.000000
  mean   1.500000
  std    0.707107
  min    1.000000
  25%    1.250000
  50%    1.500000
  75%    1.750000
  max    2.000000
2 count  2.000000
  mean   3.500000
  std    0.707107
  min    3.000000
  25%    3.250000
  50%    3.500000
  75%    3.750000
  max    4.000000

In [3]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
Out[3]:
     B
  mean       std amin amax
A
1  1.5  0.707107    1    2
2  3.5  0.707107    3    4
```

New behavior:

```
In [97]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})

In [98]: df.groupby('A').describe()
Out[98]:
      B
  count mean       std  min   25%  50%   75%  max
A
1   2.0  1.5  0.707107  1.0  1.25  1.5  1.75  2.0
2   2.0  3.5  0.707107  3.0  3.25  3.5  3.75  4.0

[2 rows x 8 columns]

In [99]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
Out[99]:
     B
  mean       std amin amax
A
1  1.5  0.707107    1    2
2  3.5  0.707107    3    4

[2 rows x 4 columns]
```

Window binary corr/cov operations return a MultiIndex DataFrame

A binary window operation, like `.corr()` or `.cov()`, when operating on a `.rolling(..)`, `.expanding(..)`, or `.ewm(..)` object, will now return a 2-level `MultiIndexed DataFrame` rather than a `Panel`, as `Panel` is now deprecated, see *here*. These are equivalent in function, but a MultiIndexed `DataFrame` enjoys more support in pandas. See the section on *Windowed Binary Operations* for more information. (GH15677)

```
In [100]: np.random.seed(1234)

In [101]: df = pd.DataFrame(np.random.rand(100, 2),
   .....:                   columns=pd.Index(['A', 'B'], name='bar'),
   .....:                   index=pd.date_range('20160101',
   .....:                                       periods=100, freq='D', name='foo'))
   .....:

In [102]: df.tail()
Out[102]:
bar                 A         B
foo
2016-04-05  0.640880  0.126205
2016-04-06  0.171465  0.737086
2016-04-07  0.127029  0.369650
2016-04-08  0.604334  0.103104
2016-04-09  0.802374  0.945553

[5 rows x 2 columns]
```

Previous behavior:

```
In [2]: df.rolling(12).corr()
Out[2]:
<class 'pandas.core.panel.Panel'>
Dimensions: 100 (items) x 2 (major_axis) x 2 (minor_axis)
Items axis: 2016-01-01 00:00:00 to 2016-04-09 00:00:00
Major_axis axis: A to B
Minor_axis axis: A to B
```

New behavior:

```
In [103]: res = df.rolling(12).corr()

In [104]: res.tail()
Out[104]:
bar                   A         B
foo        bar
2016-04-07 B   -0.132090  1.000000
2016-04-08 A    1.000000 -0.145775
           B   -0.145775  1.000000
2016-04-09 A    1.000000  0.119645
           B    0.119645  1.000000

[5 rows x 2 columns]
```

Retrieving a correlation matrix for a cross-section

```
In [105]: df.rolling(12).corr().loc['2016-04-07']
Out[105]:
```

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```
bar                   A        B
foo        bar
2016-04-07 A    1.00000 -0.13209
           B   -0.13209  1.00000

[2 rows x 2 columns]
```

HDFStore where string comparison

In previous versions most types could be compared to string column in a `HDFStore` usually resulting in an invalid comparison, returning an empty result frame. These comparisons will now raise a `TypeError` (GH15492)

```
In [106]: df = pd.DataFrame({'unparsed_date': ['2014-01-01', '2014-01-01']})

In [107]: df.to_hdf('store.h5', 'key', format='table', data_columns=True)

In [108]: df.dtypes
Out[108]:
unparsed_date    object
Length: 1, dtype: object
```

Previous behavior:

```
In [4]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
File "<string>", line 1
  (unparsed_date > 1970-01-01 00:00:01.388552400)
                 ^
SyntaxError: invalid token
```

New behavior:

```
In [18]: ts = pd.Timestamp('2014-01-01')

In [19]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
TypeError: Cannot compare 2014-01-01 00:00:00 of
type <class 'pandas.tslib.Timestamp'> to string column
```

Index.intersection and inner join now preserve the order of the left Index

`Index.intersection()` now preserves the order of the calling `Index` (left) instead of the other `Index` (right) (GH15582). This affects inner joins, *`DataFrame.join()`* and *`merge()`*, and the `.align` method.

- `Index.intersection`

```
In [109]: left = pd.Index([2, 1, 0])

In [110]: left
Out[110]: Int64Index([2, 1, 0], dtype='int64')

In [111]: right = pd.Index([1, 2, 3])

In [112]: right
Out[112]: Int64Index([1, 2, 3], dtype='int64')
```

Previous behavior:

```
In [4]: left.intersection(right)
Out[4]: Int64Index([1, 2], dtype='int64')
```

New behavior:

```
In [113]: left.intersection(right)
Out[113]: Int64Index([2, 1], dtype='int64')
```

- `DataFrame.join` and `pd.merge`

```
In [114]: left = pd.DataFrame({'a': [20, 10, 0]}, index=[2, 1, 0])

In [115]: left
Out[115]:
    a
2  20
1  10
0   0

[3 rows x 1 columns]

In [116]: right = pd.DataFrame({'b': [100, 200, 300]}, index=[1, 2, 3])

In [117]: right
Out[117]:
     b
1  100
2  200
3  300

[3 rows x 1 columns]
```

Previous behavior:

```
In [4]: left.join(right, how='inner')
Out[4]:
   a    b
1  10  100
2  20  200
```

New behavior:

```
In [118]: left.join(right, how='inner')
Out[118]:
    a    b
2  20  200
1  10  100

[2 rows x 2 columns]
```

Pivot table always returns a DataFrame

The documentation for *pivot_table()* states that a DataFrame is *always* returned. Here a bug is fixed that allowed this to return a Series under certain circumstance. (GH4386)

```
In [119]: df = pd.DataFrame({'col1': [3, 4, 5],
   .....:                    'col2': ['C', 'D', 'E'],
   .....:                    'col3': [1, 3, 9]})
   .....:

In [120]: df
Out[120]:
   col1 col2  col3
0     3    C     1
1     4    D     3
2     5    E     9

[3 rows x 3 columns]
```

Previous behavior:

```
In [2]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[2]:
col3  col2
1     C       3
3     D       4
9     E       5
Name: col1, dtype: int64
```

New behavior:

```
In [121]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[121]:
            col1
col3 col2
1    C         3
3    D         4
9    E         5

[3 rows x 1 columns]
```

Other API changes

- numexpr version is now required to be >= 2.4.6 and it will not be used at all if this requisite is not fulfilled (GH15213).
- CParserError has been renamed to ParserError in pd.read_csv() and will be removed in the future (GH12665)
- SparseArray.cumsum() and SparseSeries.cumsum() will now always return SparseArray and SparseSeries respectively (GH12855)
- DataFrame.applymap() with an empty DataFrame will return a copy of the empty DataFrame instead of a Series (GH8222)
- Series.map() now respects default values of dictionary subclasses with a __missing__ method, such as collections.Counter (GH15999)

- `.loc` has compat with `.ix` for accepting iterators, and NamedTuples (GH15120)
- `interpolate()` and `fillna()` will raise a `ValueError` if the `limit` keyword argument is not greater than 0. (GH9217)
- `pd.read_csv()` will now issue a `ParserWarning` whenever there are conflicting values provided by the `dialect` parameter and the user (GH14898)
- `pd.read_csv()` will now raise a `ValueError` for the C engine if the quote character is larger than one byte (GH11592)
- `inplace` arguments now require a boolean value, else a `ValueError` is thrown (GH14189)
- `pandas.api.types.is_datetime64_ns_dtype` will now report `True` on a tz-aware dtype, similar to `pandas.api.types.is_datetime64_any_dtype`
- `DataFrame.asof()` will return a null filled `Series` instead the scalar `NaN` if a match is not found (GH15118)
- Specific support for `copy.copy()` and `copy.deepcopy()` functions on NDFrame objects (GH15444)
- `Series.sort_values()` accepts a one element list of bool for consistency with the behavior of `DataFrame.sort_values()` (GH15604)
- `.merge()` and `.join()` on `category` dtype columns will now preserve the category dtype when possible (GH10409)
- `SparseDataFrame.default_fill_value` will be 0, previously was `nan` in the return from `pd.get_dummies(..., sparse=True)` (GH15594)
- The default behaviour of `Series.str.match` has changed from extracting groups to matching the pattern. The extracting behaviour was deprecated since pandas version 0.13.0 and can be done with the `Series.str.extract` method (GH5224). As a consequence, the `as_indexer` keyword is ignored (no longer needed to specify the new behaviour) and is deprecated.
- `NaT` will now correctly report `False` for datetimelike boolean operations such as `is_month_start` (GH15781)
- `NaT` will now correctly return `np.nan` for `Timedelta` and `Period` accessors such as `days` and `quarter` (GH15782)
- `NaT` will now returns `NaT` for `tz_localize` and `tz_convert` methods (GH15830)
- `DataFrame` and `Panel` constructors with invalid input will now raise `ValueError` rather than `PandasError`, if called with scalar inputs and not axes (GH15541)
- `DataFrame` and `Panel` constructors with invalid input will now raise `ValueError` rather than `pandas.core.common.PandasError`, if called with scalar inputs and not axes; The exception `PandasError` is removed as well. (GH15541)
- The exception `pandas.core.common.AmbiguousIndexError` is removed as it is not referenced (GH15541)

Reorganization of the library: privacy changes

Modules privacy has changed

Some formerly public python/c/c++/cython extension modules have been moved and/or renamed. These are all removed from the public API. Furthermore, the `pandas.core`, `pandas.compat`, and `pandas.util` top-level modules are now considered to be PRIVATE. If indicated, a deprecation warning will be issued if you reference these modules. (GH12588)

Previous Location	New Location	Deprecated
pandas.lib	pandas._libs.lib	X
pandas.tslib	pandas._libs.tslib	X
pandas.computation	pandas.core.computation	X
pandas.msgpack	pandas.io.msgpack	
pandas.index	pandas._libs.index	
pandas.algos	pandas._libs.algos	
pandas.hashtable	pandas._libs.hashtable	
pandas.indexes	pandas.core.indexes	
pandas.json	pandas._libs.json / pandas.io.json	X
pandas.parser	pandas._libs.parsers	X
pandas.formats	pandas.io.formats	
pandas.sparse	pandas.core.sparse	
pandas.tools	pandas.core.reshape	X
pandas.types	pandas.core.dtypes	X
pandas.io.sas.saslib	pandas.io.sas._sas	
pandas._join	pandas._libs.join	
pandas._hash	pandas._libs.hashing	
pandas._period	pandas._libs.period	
pandas._sparse	pandas._libs.sparse	
pandas._testing	pandas._libs.testing	
pandas._window	pandas._libs.window	

Some new subpackages are created with public functionality that is not directly exposed in the top-level namespace: `pandas.errors`, `pandas.plotting` and `pandas.testing` (more details below). Together with `pandas.api.types` and certain functions in the `pandas.io` and `pandas.tseries` submodules, these are now the public subpackages.

Further changes:

- The function *`union_categoricals()`* is now importable from `pandas.api.types`, formerly from `pandas.types.concat` (GH15998)
- The type import `pandas.tslib.NaTType` is deprecated and can be replaced by using `type(pandas.NaT)` (GH16146)
- The public functions in `pandas.tools.hashing` deprecated from that locations, but are now importable from `pandas.util` (GH16223)
- The modules in `pandas.util`: `decorators`, `print_versions`, `doctools`, `validators`, `depr_module` are now private. Only the functions exposed in `pandas.util` itself are public (GH16223)

pandas.errors

We are adding a standard public module for all pandas exceptions & warnings `pandas.errors`. (GH14800). Previously these exceptions & warnings could be imported from `pandas.core.common` or `pandas.io.common`. These exceptions and warnings will be removed from the `*.common` locations in a future release. (GH15541)

The following are now part of this API:

```
['DtypeWarning',
 'EmptyDataError',
 'OutOfBoundsDatetime',
 'ParserError',
 'ParserWarning',
 'PerformanceWarning',
 'UnsortedIndexError',
 'UnsupportedFunctionCall']
```

pandas.testing

We are adding a standard module that exposes the public testing functions in `pandas.testing` (GH9895). Those functions can be used when writing tests for functionality using pandas objects.

The following testing functions are now part of this API:

- *testing.assert_frame_equal()*
- *testing.assert_series_equal()*
- *testing.assert_index_equal()*

pandas.plotting

A new public `pandas.plotting` module has been added that holds plotting functionality that was previously in either `pandas.tools.plotting` or in the top-level namespace. See the *deprecations sections* for more details.

Other development changes

- Building pandas for development now requires `cython >= 0.23` (GH14831)
- Require at least 0.23 version of cython to avoid problems with character encodings (GH14699)
- Switched the test framework to use pytest (GH13097)
- Reorganization of tests directory layout (GH14854, GH15707).

Deprecations

Deprecate `.ix`

The `.ix` indexer is deprecated, in favor of the more strict `.iloc` and `.loc` indexers. `.ix` offers a lot of magic on the inference of what the user wants to do. To wit, `.ix` can decide to index *positionally* OR via *labels*, depending on the data type of the index. This has caused quite a bit of user confusion over the years. The full indexing documentation is *here*. (GH14218)

The recommended methods of indexing are:

- `.loc` if you want to *label* index
- `.iloc` if you want to *positionally* index.

Using `.ix` will now show a `DeprecationWarning` with a link to some examples of how to convert code here.

```
In [122]: df = pd.DataFrame({'A': [1, 2, 3],
   .....:                    'B': [4, 5, 6]},
   .....:                   index=list('abc'))
   .....:

In [123]: df
Out[123]:
   A  B
a  1  4
b  2  5
c  3  6

[3 rows x 2 columns]
```

Previous behavior, where you wish to get the 0th and the 2nd elements from the index in the 'A' column.

```
In [3]: df.ix[[0, 2], 'A']
Out[3]:
a    1
c    3
Name: A, dtype: int64
```

Using `.loc`. Here we will select the appropriate indexes from the index, then use *label* indexing.

```
In [124]: df.loc[df.index[[0, 2]], 'A']
Out[124]:
a    1
c    3
Name: A, Length: 2, dtype: int64
```

Using `.iloc`. Here we will get the location of the 'A' column, then use *positional* indexing to select things.

```
In [125]: df.iloc[[0, 2], df.columns.get_loc('A')]
Out[125]:
a    1
c    3
Name: A, Length: 2, dtype: int64
```

Deprecate Panel

`Panel` is deprecated and will be removed in a future version. The recommended way to represent 3-D data are with a `MultiIndex` on a `DataFrame` via the `to_frame()` or with the xarray package. pandas provides a `to_xarray()` method to automate this conversion (GH13563).

```
In [133]: import pandas._testing as tm

In [134]: p = tm.makePanel()

In [135]: p
Out[135]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

Convert to a MultiIndex DataFrame

```
In [136]: p.to_frame()
Out[136]:
                     ItemA     ItemB     ItemC
major      minor
2000-01-03 A      0.628776 -1.409432  0.209395
           B      0.988138 -1.347533 -0.896581
           C     -0.938153  1.272395 -0.161137
           D     -0.223019 -0.591863 -1.051539
2000-01-04 A      0.186494  1.422986 -0.592886
           B     -0.072608  0.363565  1.104352
           C     -1.239072 -1.449567  0.889157
           D      2.123692 -0.414505 -0.319561
2000-01-05 A      0.952478 -2.147855 -1.473116
           B     -0.550603 -0.014752 -0.431550
           C      0.139683 -1.195524  0.288377
           D      0.122273 -1.425795 -0.619993

[12 rows x 3 columns]
```

Convert to an xarray DataArray

```
In [137]: p.to_xarray()
Out[137]:
<xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)>
array([[[ 0.628776,  0.988138, -0.938153, -0.223019],
        [ 0.186494, -0.072608, -1.239072,  2.123692],
        [ 0.952478, -0.550603,  0.139683,  0.122273]],

       [[-1.409432, -1.347533,  1.272395, -0.591863],
        [ 1.422986,  0.363565, -1.449567, -0.414505],
        [-2.147855, -0.014752, -1.195524, -1.425795]],

       [[ 0.209395, -0.896581, -0.161137, -1.051539],
        [-0.592886,  1.104352,  0.889157, -0.319561],
        [-1.473116, -0.43155 ,  0.288377, -0.619993]]])
Coordinates:
  * items       (items) object 'ItemA' 'ItemB' 'ItemC'
```

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```
  * major_axis  (major_axis) datetime64[ns] 2000-01-03 2000-01-04 2000-01-05
  * minor_axis  (minor_axis) object 'A' 'B' 'C' 'D'
```

Deprecate groupby.agg() with a dictionary when renaming

The `.groupby(..).agg(..)`, `.rolling(..).agg(..)`, and `.resample(..).agg(..)` syntax can accept a variable of inputs, including scalars, list, and a dict of column names to scalars or lists. This provides a useful syntax for constructing multiple (potentially different) aggregations.

However, `.agg(..)` can *also* accept a dict that allows 'renaming' of the result columns. This is a complicated and confusing syntax, as well as not consistent between `Series` and `DataFrame`. We are deprecating this 'renaming' functionality.

- We are deprecating passing a dict to a grouped/rolled/resampled `Series`. This allowed one to `rename` the resulting aggregation, but this had a completely different meaning than passing a dictionary to a grouped `DataFrame`, which accepts column-to-aggregations.
- We are deprecating passing a dict-of-dicts to a grouped/rolled/resampled `DataFrame` in a similar manner.

This is an illustrative example:

```
In [126]: df = pd.DataFrame({'A': [1, 1, 1, 2, 2],
   .....:                    'B': range(5),
   .....:                    'C': range(5)})
   .....:

In [127]: df
Out[127]:
   A  B  C
0  1  0  0
1  1  1  1
2  1  2  2
3  2  3  3
4  2  4  4

[5 rows x 3 columns]
```

Here is a typical useful syntax for computing different aggregations for different columns. This is a natural, and useful syntax. We aggregate from the dict-to-list by taking the specified columns and applying the list of functions. This returns a `MultiIndex` for the columns (this is *not* deprecated).

```
In [128]: df.groupby('A').agg({'B': 'sum', 'C': 'min'})
Out[128]:
   B  C
A
1  3  0
2  7  3

[2 rows x 2 columns]
```

Here's an example of the first deprecation, passing a dict to a grouped `Series`. This is a combination aggregation & renaming:

```
In [6]: df.groupby('A').B.agg({'foo': 'count'})
FutureWarning: using a dict on a Series for aggregation
```

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```
is deprecated and will be removed in a future version

Out[6]:
   foo
A
1    3
2    2
```

You can accomplish the same operation, more idiomatically by:

```
In [129]: df.groupby('A').B.agg(['count']).rename(columns={'count': 'foo'})
Out[129]:
   foo
A
1    3
2    2

[2 rows x 1 columns]
```

Here's an example of the second deprecation, passing a dict-of-dict to a grouped `DataFrame`:

```
In [23]: (df.groupby('A')
    ...:    .agg({'B': {'foo': 'sum'}, 'C': {'bar': 'min'}})
    ...: )
FutureWarning: using a dict with renaming is deprecated and
will be removed in a future version

Out[23]:
     B   C
   foo bar
A
1    3   0
2    7   3
```

You can accomplish nearly the same by:

```
In [130]: (df.groupby('A')
   .....:    .agg({'B': 'sum', 'C': 'min'})
   .....:    .rename(columns={'B': 'foo', 'C': 'bar'})
   .....:  )
   .....:
Out[130]:
   foo  bar
A
1    3    0
2    7    3

[2 rows x 2 columns]
```

Deprecate .plotting

The `pandas.tools.plotting` module has been deprecated, in favor of the top level `pandas.plotting` module. All the public plotting functions are now available from `pandas.plotting` (GH12548).

Furthermore, the top-level `pandas.scatter_matrix` and `pandas.plot_params` are deprecated. Users can import these from `pandas.plotting` as well.

Previous script:

```
pd.tools.plotting.scatter_matrix(df)
pd.scatter_matrix(df)
```

Should be changed to:

```
pd.plotting.scatter_matrix(df)
```

Other deprecations

- `SparseArray.to_dense()` has deprecated the `fill` parameter, as that parameter was not being respected (GH14647)
- `SparseSeries.to_dense()` has deprecated the `sparse_only` parameter (GH14647)
- `Series.repeat()` has deprecated the `reps` parameter in favor of `repeats` (GH12662)
- The `Series` constructor and `.astype` method have deprecated accepting timestamp dtypes without a frequency (e.g. `np.datetime64`) for the `dtype` parameter (GH15524)
- `Index.repeat()` and `MultiIndex.repeat()` have deprecated the `n` parameter in favor of `repeats` (GH12662)
- `Categorical.searchsorted()` and `Series.searchsorted()` have deprecated the `v` parameter in favor of `value` (GH12662)
- `TimedeltaIndex.searchsorted()`, `DatetimeIndex.searchsorted()`, and `PeriodIndex.searchsorted()` have deprecated the `key` parameter in favor of `value` (GH12662)
- `DataFrame.astype()` has deprecated the `raise_on_error` parameter in favor of `errors` (GH14878)
- `Series.sortlevel` and `DataFrame.sortlevel` have been deprecated in favor of `Series.sort_index` and `DataFrame.sort_index` (GH15099)
- importing `concat` from `pandas.tools.merge` has been deprecated in favor of imports from the `pandas` namespace. This should only affect explicit imports (GH15358)
- `Series/DataFrame/Panel.consolidate()` been deprecated as a public method. (GH15483)
- The `as_indexer` keyword of `Series.str.match()` has been deprecated (ignored keyword) (GH15257).
- The following top-level pandas functions have been deprecated and will be removed in a future version (GH13790, GH15940)
  - `pd.pnow()`, replaced by `Period.now()`
  - `pd.Term`, is removed, as it is not applicable to user code. Instead use in-line string expressions in the where clause when searching in HDFStore
  - `pd.Expr`, is removed, as it is not applicable to user code.
  - `pd.match()`, is removed.

  - `pd.groupby()`, replaced by using the `.groupby()` method directly on a `Series/DataFrame`
  - `pd.get_store()`, replaced by a direct call to `pd.HDFStore(...)`

- `is_any_int_dtype`, `is_floating_dtype`, and `is_sequence` are deprecated from `pandas.api.types` (GH16042)

Removal of prior version deprecations/changes

- The `pandas.rpy` module is removed. Similar functionality can be accessed through the rpy2 project. See the R interfacing docs for more details.
- The `pandas.io.ga` module with a `google-analytics` interface is removed (GH11308). Similar functionality can be found in the Google2Pandas package.
- `pd.to_datetime` and `pd.to_timedelta` have dropped the `coerce` parameter in favor of `errors` (GH13602)
- `pandas.stats.fama_macbeth`, `pandas.stats.ols`, `pandas.stats.plm` and `pandas.stats.var`, as well as the top-level `pandas.fama_macbeth` and `pandas.ols` routines are removed. Similar functionality can be found in the statsmodels package. (GH11898)
- The `TimeSeries` and `SparseTimeSeries` classes, aliases of `Series` and `SparseSeries`, are removed (GH10890, GH15098).
- `Series.is_time_series` is dropped in favor of `Series.index.is_all_dates` (GH15098)
- The deprecated `irow`, `icol`, `iget` and `iget_value` methods are removed in favor of `iloc` and `iat` as explained *here* (GH10711).
- The deprecated `DataFrame.iterkv()` has been removed in favor of `DataFrame.iteritems()` (GH10711)
- The `Categorical` constructor has dropped the `name` parameter (GH10632)
- `Categorical` has dropped support for `NaN` categories (GH10748)
- The `take_last` parameter has been dropped from `duplicated()`, `drop_duplicates()`, `nlargest()`, and `nsmallest()` methods (GH10236, GH10792, GH10920)
- `Series`, `Index`, and `DataFrame` have dropped the `sort` and `order` methods (GH10726)
- Where clauses in `pytables` are only accepted as strings and expressions types and not other data-types (GH12027)
- `DataFrame` has dropped the `combineAdd` and `combineMult` methods in favor of `add` and `mul` respectively (GH10735)

Performance improvements

- Improved performance of `pd.wide_to_long()` (GH14779)
- Improved performance of `pd.factorize()` by releasing the GIL with `object` dtype when inferred as strings (GH14859, GH16057)
- Improved performance of timeseries plotting with an irregular DatetimeIndex (or with `compat_x=True`) (GH15073).
- Improved performance of `groupby().cummin()` and `groupby().cummax()` (GH15048, GH15109, GH15561, GH15635)
- Improved performance and reduced memory when indexing with a `MultiIndex` (GH15245)

- When reading buffer object in `read_sas()` method without specified format, filepath string is inferred rather than buffer object. (GH14947)
- Improved performance of `.rank()` for categorical data (GH15498)
- Improved performance when using `.unstack()` (GH15503)
- Improved performance of merge/join on `category` columns (GH10409)
- Improved performance of `drop_duplicates()` on `bool` columns (GH12963)
- Improve performance of `pd.core.groupby.GroupBy.apply` when the applied function used the `.name` attribute of the group DataFrame (GH15062).
- Improved performance of `iloc` indexing with a list or array (GH15504).
- Improved performance of `Series.sort_index()` with a monotonic index (GH15694)
- Improved performance in `pd.read_csv()` on some platforms with buffered reads (GH16039)

Bug fixes

Conversion

- Bug in `Timestamp.replace` now raises `TypeError` when incorrect argument names are given; previously this raised `ValueError` (GH15240)
- Bug in `Timestamp.replace` with compat for passing long integers (GH15030)
- Bug in `Timestamp` returning UTC based time/date attributes when a timezone was provided (GH13303, GH6538)
- Bug in `Timestamp` incorrectly localizing timezones during construction (GH11481, GH15777)
- Bug in `TimedeltaIndex` addition where overflow was being allowed without error (GH14816)
- Bug in `TimedeltaIndex` raising a `ValueError` when boolean indexing with `loc` (GH14946)
- Bug in catching an overflow in `Timestamp` + `Timedelta/Offset` operations (GH15126)
- Bug in `DatetimeIndex.round()` and `Timestamp.round()` floating point accuracy when rounding by milliseconds or less (GH14440, GH15578)
- Bug in `astype()` where `inf` values were incorrectly converted to integers. Now raises error now with `astype()` for Series and DataFrames (GH14265)
- Bug in `DataFrame(..).apply(to_numeric)` when values are of type decimal.Decimal. (GH14827)
- Bug in `describe()` when passing a numpy array which does not contain the median to the `percentiles` keyword argument (GH14908)
- Cleaned up `PeriodIndex` constructor, including raising on floats more consistently (GH13277)
- Bug in using `__deepcopy__` on empty NDFrame objects (GH15370)
- Bug in `.replace()` may result in incorrect dtypes. (GH12747, GH15765)
- Bug in `Series.replace` and `DataFrame.replace` which failed on empty replacement dicts (GH15289)
- Bug in `Series.replace` which replaced a numeric by string (GH15743)
- Bug in `Index` construction with `NaN` elements and integer dtype specified (GH15187)
- Bug in `Series` construction with a datetimetz (GH14928)
- Bug in `Series.dt.round()` inconsistent behaviour on `NaT` 's with different arguments (GH14940)

- Bug in `Series` constructor when both `copy=True` and `dtype` arguments are provided (GH15125)
- Incorrect dtyped `Series` was returned by comparison methods (e.g., `lt`, `gt`, ...) against a constant for an empty `DataFrame` (GH15077)
- Bug in `Series.ffill()` with mixed dtypes containing tz-aware datetimes. (GH14956)
- Bug in `DataFrame.fillna()` where the argument `downcast` was ignored when fillna value was of type `dict` (GH15277)
- Bug in `.asfreq()`, where frequency was not set for empty `Series` (GH14320)
- Bug in `DataFrame` construction with nulls and datetimes in a list-like (GH15869)
- Bug in `DataFrame.fillna()` with tz-aware datetimes (GH15855)
- Bug in `is_string_dtype`, `is_timedelta64_ns_dtype`, and `is_string_like_dtype` in which an error was raised when `None` was passed in (GH15941)
- Bug in the return type of `pd.unique` on a `Categorical`, which was returning an ndarray and not a `Categorical` (GH15903)
- Bug in `Index.to_series()` where the index was not copied (and so mutating later would change the original), (GH15949)
- Bug in indexing with partial string indexing with a len-1 DataFrame (GH16071)
- Bug in `Series` construction where passing invalid dtype didn't raise an error. (GH15520)

Indexing

- Bug in `Index` power operations with reversed operands (GH14973)
- Bug in `DataFrame.sort_values()` when sorting by multiple columns where one column is of type `int64` and contains `NaT` (GH14922)
- Bug in `DataFrame.reindex()` in which `method` was ignored when passing `columns` (GH14992)
- Bug in `DataFrame.loc` with indexing a `MultiIndex` with a `Series` indexer (GH14730, GH15424)
- Bug in `DataFrame.loc` with indexing a `MultiIndex` with a numpy array (GH15434)
- Bug in `Series.asof` which raised if the series contained all `np.nan` (GH15713)
- Bug in `.at` when selecting from a tz-aware column (GH15822)
- Bug in `Series.where()` and `DataFrame.where()` where array-like conditionals were being rejected (GH15414)
- Bug in `Series.where()` where TZ-aware data was converted to float representation (GH15701)
- Bug in `.loc` that would not return the correct dtype for scalar access for a DataFrame (GH11617)
- Bug in output formatting of a `MultiIndex` when names are integers (GH12223, GH15262)
- Bug in `Categorical.searchsorted()` where alphabetical instead of the provided categorical order was used (GH14522)
- Bug in `Series.iloc` where a `Categorical` object for list-like indexes input was returned, where a `Series` was expected. (GH14580)
- Bug in `DataFrame.isin` comparing datetimelike to empty frame (GH15473)
- Bug in `.reset_index()` when an all `NaN` level of a `MultiIndex` would fail (GH6322)

- Bug in `.reset_index()` when raising error for index name already present in `MultiIndex` columns (GH16120)
- Bug in creating a `MultiIndex` with tuples and not passing a list of names; this will now raise `ValueError` (GH15110)
- Bug in the HTML display with a `MultiIndex` and truncation (GH14882)
- Bug in the display of `.info()` where a qualifier (+) would always be displayed with a `MultiIndex` that contains only non-strings (GH15245)
- Bug in `pd.concat()` where the names of `MultiIndex` of resulting `DataFrame` are not handled correctly when `None` is presented in the names of `MultiIndex` of input `DataFrame` (GH15787)
- Bug in `DataFrame.sort_index()` and `Series.sort_index()` where `na_position` doesn't work with a `MultiIndex` (GH14784, GH16604)
- Bug in `pd.concat()` when combining objects with a `CategoricalIndex` (GH16111)
- Bug in indexing with a scalar and a `CategoricalIndex` (GH16123)

IO

- Bug in `pd.to_numeric()` in which float and unsigned integer elements were being improperly casted (GH14941, GH15005)
- Bug in `pd.read_fwf()` where the skiprows parameter was not being respected during column width inference (GH11256)
- Bug in `pd.read_csv()` in which the `dialect` parameter was not being verified before processing (GH14898)
- Bug in `pd.read_csv()` in which missing data was being improperly handled with `usecols` (GH6710)
- Bug in `pd.read_csv()` in which a file containing a row with many columns followed by rows with fewer columns would cause a crash (GH14125)
- Bug in `pd.read_csv()` for the C engine where `usecols` were being indexed incorrectly with `parse_dates` (GH14792)
- Bug in `pd.read_csv()` with `parse_dates` when multi-line headers are specified (GH15376)
- Bug in `pd.read_csv()` with `float_precision='round_trip'` which caused a segfault when a text entry is parsed (GH15140)
- Bug in `pd.read_csv()` when an index was specified and no values were specified as null values (GH15835)
- Bug in `pd.read_csv()` in which certain invalid file objects caused the Python interpreter to crash (GH15337)
- Bug in `pd.read_csv()` in which invalid values for `nrows` and `chunksize` were allowed (GH15767)
- Bug in `pd.read_csv()` for the Python engine in which unhelpful error messages were being raised when parsing errors occurred (GH15910)
- Bug in `pd.read_csv()` in which the `skipfooter` parameter was not being properly validated (GH15925)
- Bug in `pd.to_csv()` in which there was numeric overflow when a timestamp index was being written (GH15982)
- Bug in `pd.util.hashing.hash_pandas_object()` in which hashing of categoricals depended on the ordering of categories, instead of just their values. (GH15143)
- Bug in `.to_json()` where `lines=True` and contents (keys or values) contain escaped characters (GH15096)

- Bug in `.to_json()` causing single byte ascii characters to be expanded to four byte unicode (GH15344)
- Bug in `.to_json()` for the C engine where rollover was not correctly handled for case where frac is odd and diff is exactly 0.5 (GH15716, GH15864)
- Bug in `pd.read_json()` for Python 2 where `lines=True` and contents contain non-ascii unicode characters (GH15132)
- Bug in `pd.read_msgpack()` in which `Series` categoricals were being improperly processed (GH14901)
- Bug in `pd.read_msgpack()` which did not allow loading of a dataframe with an index of type `CategoricalIndex` (GH15487)
- Bug in `pd.read_msgpack()` when deserializing a `CategoricalIndex` (GH15487)
- Bug in `DataFrame.to_records()` with converting a `DatetimeIndex` with a timezone (GH13937)
- Bug in `DataFrame.to_records()` which failed with unicode characters in column names (GH11879)
- Bug in `.to_sql()` when writing a DataFrame with numeric index names (GH15404).
- Bug in `DataFrame.to_html()` with `index=False` and `max_rows` raising in `IndexError` (GH14998)
- Bug in `pd.read_hdf()` passing a `Timestamp` to the `where` parameter with a non date column (GH15492)
- Bug in `DataFrame.to_stata()` and `StataWriter` which produces incorrectly formatted files to be produced for some locales (GH13856)
- Bug in `StataReader` and `StataWriter` which allows invalid encodings (GH15723)
- Bug in the `Series` repr not showing the length when the output was truncated (GH15962).

Plotting

- Bug in `DataFrame.hist` where `plt.tight_layout` caused an `AttributeError` (use `matplotlib >= 2.0.1`) (GH9351)
- Bug in `DataFrame.boxplot` where `fontsize` was not applied to the tick labels on both axes (GH15108)
- Bug in the date and time converters pandas registers with matplotlib not handling multiple dimensions (GH16026)
- Bug in `pd.scatter_matrix()` could accept either `color` or `c`, but not both (GH14855)

GroupBy/resample/rolling

- Bug in `.groupby(..).resample()` when passed the `on=` kwarg. (GH15021)
- Properly set `__name__` and `__qualname__` for `Groupby.*` functions (GH14620)
- Bug in `GroupBy.get_group()` failing with a categorical grouper (GH15155)
- Bug in `.groupby(...).rolling(...)` when `on` is specified and using a `DatetimeIndex` (GH15130, GH13966)
- Bug in groupby operations with `timedelta64` when passing `numeric_only=False` (GH5724)
- Bug in `groupby.apply()` coercing `object` dtypes to numeric types, when not all values were numeric (GH14423, GH15421, GH15670)
- Bug in `resample`, where a non-string `loffset` argument would not be applied when resampling a timeseries (GH13218)

- Bug in `DataFrame.groupby().describe()` when grouping on `Index` containing tuples (GH14848)
- Bug in `groupby().nunique()` with a datetimelike-grouper where bins counts were incorrect (GH13453)
- Bug in `groupby.transform()` that would coerce the resultant dtypes back to the original (GH10972, GH11444)
- Bug in `groupby.agg()` incorrectly localizing timezone on `datetime` (GH15426, GH10668, GH13046)
- Bug in `.rolling/expanding()` functions where `count()` was not counting `np.Inf`, nor handling `object` dtypes (GH12541)
- Bug in `.rolling()` where `pd.Timedelta` or `datetime.timedelta` was not accepted as a `window` argument (GH15440)
- Bug in `Rolling.quantile` function that caused a segmentation fault when called with a quantile value outside of the range [0, 1] (GH15463)
- Bug in `DataFrame.resample().median()` if duplicate column names are present (GH14233)

Sparse

- Bug in `SparseSeries.reindex` on single level with list of length 1 (GH15447)
- Bug in repr-formatting a `SparseDataFrame` after a value was set on (a copy of) one of its series (GH15488)
- Bug in `SparseDataFrame` construction with lists not coercing to dtype (GH15682)
- Bug in sparse array indexing in which indices were not being validated (GH15863)

Reshaping

- Bug in `pd.merge_asof()` where `left_index` or `right_index` caused a failure when multiple `by` was specified (GH15676)
- Bug in `pd.merge_asof()` where `left_index/right_index` together caused a failure when `tolerance` was specified (GH15135)
- Bug in `DataFrame.pivot_table()` where `dropna=True` would not drop all-NaN columns when the columns was a `category` dtype (GH15193)
- Bug in `pd.melt()` where passing a tuple value for `value_vars` caused a `TypeError` (GH15348)
- Bug in `pd.pivot_table()` where no error was raised when values argument was not in the columns (GH14938)
- Bug in `pd.concat()` in which concatenating with an empty dataframe with `join='inner'` was being improperly handled (GH15328)
- Bug with `sort=True` in `DataFrame.join` and `pd.merge` when joining on indexes (GH15582)
- Bug in `DataFrame.nsmallest` and `DataFrame.nlargest` where identical values resulted in duplicated rows (GH15297)
- Bug in *`pandas.pivot_table()`* incorrectly raising `UnicodeError` when passing unicode input for `margins` keyword (GH13292)

Numeric

- Bug in `.rank()` which incorrectly ranks ordered categories (GH15420)
- Bug in `.corr()` and `.cov()` where the column and index were the same object (GH14617)
- Bug in `.mode()` where `mode` was not returned if was only a single value (GH15714)
- Bug in `pd.cut()` with a single bin on an all 0s array (GH15428)
- Bug in `pd.qcut()` with a single quantile and an array with identical values (GH15431)
- Bug in `pandas.tools.utils.cartesian_product()` with large input can cause overflow on windows (GH15265)
- Bug in `.eval()` which caused multi-line evals to fail with local variables not on the first line (GH15342)

Other

- Compat with SciPy 0.19.0 for testing on `.interpolate()` (GH15662)
- Compat for 32-bit platforms for `.qcut/cut`; bins will now be `int64` dtype (GH14866)
- Bug in interactions with `Qt` when a `QtApplication` already exists (GH14372)
- Avoid use of `np.finfo()` during `import pandas` removed to mitigate deadlock on Python GIL misuse (GH14641)

Contributors

A total of 204 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- manuels +
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- pbreach +
- sakkemo +
- scls19fr
- sinhrks
- stijnvanhoey +
- the-nose-knows +

- themrmax +
- tomrod +
- tzinckgraf
- wandersoncferreira
- watercrossing +
- wcwagner
- xgdgsc +
- yui-knk

5.10 Version 0.19

5.10.1 Version 0.19.2 (December 24, 2016)

This is a minor bug-fix release in the 0.19.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Compatibility with Python 3.6
- Added a Pandas Cheat Sheet. (GH13202).

What's new in v0.19.2

- *Enhancements*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

Enhancements

The `pd.merge_asof()`, added in 0.19.0, gained some improvements:

- `pd.merge_asof()` gained `left_index`/`right_index` and `left_by`/`right_by` arguments (GH14253)
- `pd.merge_asof()` can take multiple columns in `by` parameter and has specialized dtypes for better performance (GH13936)

Performance improvements

- Performance regression with `PeriodIndex` (GH14822)
- Performance regression in indexing with getitem (GH14930)
- Improved performance of `.replace()` (GH12745)
- Improved performance `Series` creation with a datetime index and dictionary data (GH14894)

Bug fixes

- Compat with python 3.6 for pickling of some offsets (GH14685)
- Compat with python 3.6 for some indexing exception types (GH14684, GH14689)
- Compat with python 3.6 for deprecation warnings in the test suite (GH14681)
- Compat with python 3.6 for Timestamp pickles (GH14689)
- Compat with `dateutil==2.6.0`; segfault reported in the testing suite (GH14621)
- Allow `nanoseconds` in `Timestamp.replace` as a kwarg (GH14621)
- Bug in `pd.read_csv` in which aliasing was being done for `na_values` when passed in as a dictionary (GH14203)
- Bug in `pd.read_csv` in which column indices for a dict-like `na_values` were not being respected (GH14203)
- Bug in `pd.read_csv` where reading files fails, if the number of headers is equal to the number of lines in the file (GH14515)
- Bug in `pd.read_csv` for the Python engine in which an unhelpful error message was being raised when multi-char delimiters were not being respected with quotes (GH14582)
- Fix bugs (GH14734, GH13654) in `pd.read_sas` and `pandas.io.sas.sas7bdat.SAS7BDATReader` that caused problems when reading a SAS file incrementally.
- Bug in `pd.read_csv` for the Python engine in which an unhelpful error message was being raised when `skipfooter` was not being respected by Python's CSV library (GH13879)
- Bug in `.fillna()` in which timezone aware datetime64 values were incorrectly rounded (GH14872)
- Bug in `.groupby(..., sort=True)` of a non-lexsorted MultiIndex when grouping with multiple levels (GH14776)
- Bug in `pd.cut` with negative values and a single bin (GH14652)
- Bug in `pd.to_numeric` where a 0 was not unsigned on a `downcast='unsigned'` argument (GH14401)
- Bug in plotting regular and irregular timeseries using shared axes (`sharex=True` or `ax.twinx()`) (GH13341, GH14322).
- Bug in not propagating exceptions in parsing invalid datetimes, noted in python 3.6 (GH14561)
- Bug in resampling a `DatetimeIndex` in local TZ, covering a DST change, which would raise `AmbiguousTimeError` (GH14682)
- Bug in indexing that transformed `RecursionError` into `KeyError` or `IndexingError` (GH14554)
- Bug in `HDFStore` when writing a `MultiIndex` when using `data_columns=True` (GH14435)
- Bug in `HDFStore.append()` when writing a `Series` and passing a `min_itemsize` argument containing a value for the `index` (GH11412)

- Bug when writing to a `HDFStore` in `table` format with a `min_itemsize` value for the `index` and without asking to append (GH10381)
- Bug in `Series.groupby.nunique()` raising an `IndexError` for an empty `Series` (GH12553)
- Bug in `DataFrame.nlargest` and `DataFrame.nsmallest` when the index had duplicate values (GH13412)
- Bug in clipboard functions on linux with python2 with unicode and separators (GH13747)
- Bug in clipboard functions on Windows 10 and python 3 (GH14362, GH12807)
- Bug in `.to_clipboard()` and Excel compat (GH12529)
- Bug in `DataFrame.combine_first()` for integer columns (GH14687).
- Bug in `pd.read_csv()` in which the `dtype` parameter was not being respected for empty data (GH14712)
- Bug in `pd.read_csv()` in which the `nrows` parameter was not being respected for large input when using the C engine for parsing (GH7626)
- Bug in `pd.merge_asof()` could not handle timezone-aware DatetimeIndex when a tolerance was specified (GH14844)
- Explicit check in `to_stata` and `StataWriter` for out-of-range values when writing doubles (GH14618)
- Bug in `.plot(kind='kde')` which did not drop missing values to generate the KDE Plot, instead generating an empty plot. (GH14821)
- Bug in `unstack()` if called with a list of column(s) as an argument, regardless of the dtypes of all columns, they get coerced to `object` (GH11847)

Contributors

A total of 33 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Joris Van den Bossche
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- Keshav Ramaswamy

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5.10.2 Version 0.19.1 (November 3, 2016)

This is a minor bug-fix release from 0.19.0 and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

What's new in v0.19.1

- *Performance improvements*
- *Bug fixes*
- *Contributors*

Performance improvements

- Fixed performance regression in factorization of `Period` data (GH14338)
- Fixed performance regression in `Series.asof(where)` when `where` is a scalar (GH14461)
- Improved performance in `DataFrame.asof(where)` when `where` is a scalar (GH14461)
- Improved performance in `.to_json()` when `lines=True` (GH14408)
- Improved performance in certain types of `loc` indexing with a MultiIndex (GH14551).

Bug fixes

- Source installs from PyPI will now again work without `cython` installed, as in previous versions (GH14204)
- Compat with Cython 0.25 for building (GH14496)
- Fixed regression where user-provided file handles were closed in `read_csv` (c engine) (GH14418).
- Fixed regression in `DataFrame.quantile` when missing values where present in some columns (GH14357).
- Fixed regression in `Index.difference` where the `freq` of a `DatetimeIndex` was incorrectly set (GH14323)
- Added back `pandas.core.common.array_equivalent` with a deprecation warning (GH14555).
- Bug in `pd.read_csv` for the C engine in which quotation marks were improperly parsed in skipped rows (GH14459)
- Bug in `pd.read_csv` for Python 2.x in which Unicode quote characters were no longer being respected (GH14477)
- Fixed regression in `Index.append` when categorical indices were appended (GH14545).
- Fixed regression in `pd.DataFrame` where constructor fails when given dict with `None` value (GH14381)
- Fixed regression in `DatetimeIndex._maybe_cast_slice_bound` when index is empty (GH14354).
- Bug in localizing an ambiguous timezone when a boolean is passed (GH14402)
- Bug in `TimedeltaIndex` addition with a Datetime-like object where addition overflow in the negative direction was not being caught (GH14068, GH14453)
- Bug in string indexing against data with `object Index` may raise `AttributeError` (GH14424)
- Correctly raise `ValueError` on empty input to `pd.eval()` and `df.query()` (GH13139)
- Bug in `RangeIndex.intersection` when result is a empty set (GH14364).
- Bug in groupby-transform broadcasting that could cause incorrect dtype coercion (GH14457)
- Bug in `Series.__setitem__` which allowed mutating read-only arrays (GH14359).
- Bug in `DataFrame.insert` where multiple calls with duplicate columns can fail (GH14291)
- `pd.merge()` will raise `ValueError` with non-boolean parameters in passed boolean type arguments (GH14434)
- Bug in `Timestamp` where dates very near the minimum (1677-09) could underflow on creation (GH14415)
- Bug in `pd.concat` where names of the `keys` were not propagated to the resulting `MultiIndex` (GH14252)
- Bug in `pd.concat` where `axis` cannot take string parameters `'rows'` or `'columns'` (GH14369)
- Bug in `pd.concat` with dataframes heterogeneous in length and tuple `keys` (GH14438)
- Bug in `MultiIndex.set_levels` where illegal level values were still set after raising an error (GH13754)
- Bug in `DataFrame.to_json` where `lines=True` and a value contained a `}` character (GH14391)
- Bug in `df.groupby` causing an `AttributeError` when grouping a single index frame by a column and the index level (GH14327)
- Bug in `df.groupby` where `TypeError` raised when `pd.Grouper(key=...)` is passed in a list (GH14334)
- Bug in `pd.pivot_table` may raise `TypeError` or `ValueError` when `index` or `columns` is not scalar and `values` is not specified (GH14380)

Contributors

A total of 30 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.10.3 Version 0.19.0 (October 2, 2016)

This is a major release from 0.18.1 and includes number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `merge_asof()` for asof-style time-series joining, see *here*
- `.rolling()` is now time-series aware, see *here*
- `read_csv()` now supports parsing `Categorical` data, see *here*
- A function `union_categorical()` has been added for combining categoricals, see *here*
- `PeriodIndex` now has its own `period` dtype, and changed to be more consistent with other `Index` classes. See *here*
- Sparse data structures gained enhanced support of `int` and `bool` dtypes, see *here*
- Comparison operations with `Series` no longer ignores the index, see *here* for an overview of the API changes.
- Introduction of a pandas development API for utility functions, see *here*.
- Deprecation of `Panel4D` and `PanelND`. We recommend to represent these types of n-dimensional data with the xarray package.
- Removal of the previously deprecated modules `pandas.io.data`, `pandas.io.wb`, `pandas.tools.rplot`.

Warning: pandas >= 0.19.0 will no longer silence numpy ufunc warnings upon import, see *here*.

What's new in v0.19.0

- *New features*
  - *Function `merge_asof` for asof-style time-series joining*
  - *Method `.rolling()` is now time-series aware*
  - *Method `read_csv` has improved support for duplicate column names*
  - *Method `read_csv` supports parsing `Categorical` directly*
  - *Categorical concatenation*
  - *Semi-month offsets*
  - *New Index methods*
  - *Google BigQuery enhancements*
  - *Fine-grained NumPy errstate*
  - *Method `get_dummies` now returns integer dtypes*
  - *Downcast values to smallest possible dtype in `to_numeric`*
  - *pandas development API*
  - *Other enhancements*
- *API changes*

- *Series.tolist() will now return Python types*
- *Series operators for different indexes*
  - *Arithmetic operators*
  - *Comparison operators*
  - *Logical operators*
  - *Flexible comparison methods*
- *Series type promotion on assignment*
- *Function .to_datetime() changes*
- *Merging changes*
- *Method .describe() changes*
- *Period changes*
  - *The PeriodIndex now has period dtype*
  - *Period('NaT') now returns pd.NaT*
  - *PeriodIndex.values now returns array of Period object*
- *Index +/- no longer used for set operations*
- *Index.difference and .symmetric_difference changes*
- *Index.unique consistently returns Index*
- *MultiIndex constructors, groupby and set_index preserve categorical dtypes*
- *Function read_csv will progressively enumerate chunks*
- *Sparse changes*
  - *Types int64 and bool support enhancements*
  - *Operators now preserve dtypes*
  - *Other sparse fixes*
- *Indexer dtype changes*
- *Other API changes*

- *Deprecations*
- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

New features

Function `merge_asof` for asof-style time-series joining

A long-time requested feature has been added through the *merge_asof()* function, to support asof style joining of time-series (GH1870, GH13695, GH13709, GH13902). Full documentation is *here*.

The *merge_asof()* performs an asof merge, which is similar to a left-join except that we match on nearest key rather than equal keys.

```
In [1]: left = pd.DataFrame({"a": [1, 5, 10], "left_val": ["a", "b", "c"]})

In [2]: right = pd.DataFrame({"a": [1, 2, 3, 6, 7], "right_val": [1, 2, 3, 6, 7]})

In [3]: left
Out[3]:
    a left_val
0   1        a
1   5        b
2  10        c

[3 rows x 2 columns]

In [4]: right
Out[4]:
   a  right_val
0  1          1
1  2          2
2  3          3
3  6          6
4  7          7

[5 rows x 2 columns]
```

We typically want to match exactly when possible, and use the most recent value otherwise.

```
In [5]: pd.merge_asof(left, right, on="a")
Out[5]:
    a left_val  right_val
0   1        a          1
1   5        b          3
2  10        c          7

[3 rows x 3 columns]
```

We can also match rows ONLY with prior data, and not an exact match.

```
In [6]: pd.merge_asof(left, right, on="a", allow_exact_matches=False)
Out[6]:
    a left_val  right_val
0   1        a        NaN
1   5        b        3.0
2  10        c        7.0

[3 rows x 3 columns]
```

In a typical time-series example, we have `trades` and `quotes` and we want to `asof-join` them. This also illustrates using the `by` parameter to group data before merging.

```
In [7]: trades = pd.DataFrame(
   ...:     {
   ...:         "time": pd.to_datetime(
   ...:             [
   ...:                 "20160525 13:30:00.023",
   ...:                 "20160525 13:30:00.038",
   ...:                 "20160525 13:30:00.048",
   ...:                 "20160525 13:30:00.048",
   ...:                 "20160525 13:30:00.048",
   ...:             ]
   ...:         ),
   ...:         "ticker": ["MSFT", "MSFT", "GOOG", "GOOG", "AAPL"],
   ...:         "price": [51.95, 51.95, 720.77, 720.92, 98.00],
   ...:         "quantity": [75, 155, 100, 100, 100],
   ...:     },
   ...:     columns=["time", "ticker", "price", "quantity"],
   ...: )
   ...:

In [8]: quotes = pd.DataFrame(
   ...:     {
   ...:         "time": pd.to_datetime(
   ...:             [
   ...:                 "20160525 13:30:00.023",
   ...:                 "20160525 13:30:00.023",
   ...:                 "20160525 13:30:00.030",
   ...:                 "20160525 13:30:00.041",
   ...:                 "20160525 13:30:00.048",
   ...:                 "20160525 13:30:00.049",
   ...:                 "20160525 13:30:00.072",
   ...:                 "20160525 13:30:00.075",
   ...:             ]
   ...:         ),
   ...:         "ticker": ["GOOG", "MSFT", "MSFT", "MSFT", "GOOG", "AAPL", "GOOG",
↪"MSFT"],
   ...:         "bid": [720.50, 51.95, 51.97, 51.99, 720.50, 97.99, 720.50, 52.01],
   ...:         "ask": [720.93, 51.96, 51.98, 52.00, 720.93, 98.01, 720.88, 52.03],
   ...:     },
   ...:     columns=["time", "ticker", "bid", "ask"],
   ...: )
   ...:
```

```
In [9]: trades
Out[9]:
                     time ticker   price  quantity
0 2016-05-25 13:30:00.023   MSFT   51.95        75
1 2016-05-25 13:30:00.038   MSFT   51.95       155
2 2016-05-25 13:30:00.048   GOOG  720.77       100
3 2016-05-25 13:30:00.048   GOOG  720.92       100
4 2016-05-25 13:30:00.048   AAPL   98.00       100

[5 rows x 4 columns]

In [10]: quotes
Out[10]:
                     time ticker     bid     ask
0 2016-05-25 13:30:00.023   GOOG  720.50  720.93
```

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```
1 2016-05-25 13:30:00.023   MSFT   51.95   51.96
2 2016-05-25 13:30:00.030   MSFT   51.97   51.98
3 2016-05-25 13:30:00.041   MSFT   51.99   52.00
4 2016-05-25 13:30:00.048   GOOG  720.50  720.93
5 2016-05-25 13:30:00.049   AAPL   97.99   98.01
6 2016-05-25 13:30:00.072   GOOG  720.50  720.88
7 2016-05-25 13:30:00.075   MSFT   52.01   52.03

[8 rows x 4 columns]
```

An asof merge joins on the `on`, typically a datetimelike field, which is ordered, and in this case we are using a grouper in the `by` field. This is like a left-outer join, except that forward filling happens automatically taking the most recent non-NaN value.

```
In [11]: pd.merge_asof(trades, quotes, on="time", by="ticker")
Out[11]:
                     time ticker   price  quantity     bid     ask
0 2016-05-25 13:30:00.023   MSFT   51.95        75   51.95   51.96
1 2016-05-25 13:30:00.038   MSFT   51.95       155   51.97   51.98
2 2016-05-25 13:30:00.048   GOOG  720.77       100  720.50  720.93
3 2016-05-25 13:30:00.048   GOOG  720.92       100  720.50  720.93
4 2016-05-25 13:30:00.048   AAPL   98.00       100     NaN     NaN

[5 rows x 6 columns]
```

This returns a merged DataFrame with the entries in the same order as the original left passed DataFrame (`trades` in this case), with the fields of the `quotes` merged.

Method `.rolling()` is now time-series aware

`.rolling()` objects are now time-series aware and can accept a time-series offset (or convertible) for the `window` argument (GH13327, GH12995). See the full documentation *here*.

```
In [12]: dft = pd.DataFrame(
   ....:     {"B": [0, 1, 2, np.nan, 4]},
   ....:     index=pd.date_range("20130101 09:00:00", periods=5, freq="s"),
   ....: )
   ....:

In [13]: dft
Out[13]:
                     B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  2.0
2013-01-01 09:00:03  NaN
2013-01-01 09:00:04  4.0

[5 rows x 1 columns]
```

This is a regular frequency index. Using an integer window parameter works to roll along the window frequency.

```
In [14]: dft.rolling(2).sum()
Out[14]:
                     B
```

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```
2013-01-01 09:00:00  NaN
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  3.0
2013-01-01 09:00:03  NaN
2013-01-01 09:00:04  NaN

[5 rows x 1 columns]

In [15]: dft.rolling(2, min_periods=1).sum()
Out[15]:
                     B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  3.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:04  4.0

[5 rows x 1 columns]
```

Specifying an offset allows a more intuitive specification of the rolling frequency.

```
In [16]: dft.rolling("2s").sum()
Out[16]:
                     B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  3.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:04  4.0

[5 rows x 1 columns]
```

Using a non-regular, but still monotonic index, rolling with an integer window does not impart any special calculation.

```
In [17]: dft = pd.DataFrame(
   ....:     {"B": [0, 1, 2, np.nan, 4]},
   ....:     index=pd.Index(
   ....:         [
   ....:             pd.Timestamp("20130101 09:00:00"),
   ....:             pd.Timestamp("20130101 09:00:02"),
   ....:             pd.Timestamp("20130101 09:00:03"),
   ....:             pd.Timestamp("20130101 09:00:05"),
   ....:             pd.Timestamp("20130101 09:00:06"),
   ....:         ],
   ....:         name="foo",
   ....:     ),
   ....: )
   ....:

In [18]: dft
Out[18]:
                     B
foo
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
```

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```
2013-01-01 09:00:06  4.0

[5 rows x 1 columns]

In [19]: dft.rolling(2).sum()
Out[19]:
                       B
foo
2013-01-01 09:00:00  NaN
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  NaN

[5 rows x 1 columns]
```

Using the time-specification generates variable windows for this sparse data.

```
In [20]: dft.rolling("2s").sum()
Out[20]:
                       B
foo
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0

[5 rows x 1 columns]
```

Furthermore, we now allow an optional `on` parameter to specify a column (rather than the default of the index) in a DataFrame.

```
In [21]: dft = dft.reset_index()

In [22]: dft
Out[22]:
                   foo    B
0 2013-01-01 09:00:00  0.0
1 2013-01-01 09:00:02  1.0
2 2013-01-01 09:00:03  2.0
3 2013-01-01 09:00:05  NaN
4 2013-01-01 09:00:06  4.0

[5 rows x 2 columns]

In [23]: dft.rolling("2s", on="foo").sum()
Out[23]:
                   foo    B
0 2013-01-01 09:00:00  0.0
1 2013-01-01 09:00:02  1.0
2 2013-01-01 09:00:03  3.0
3 2013-01-01 09:00:05  NaN
4 2013-01-01 09:00:06  4.0

[5 rows x 2 columns]
```

Method `read_csv` has improved support for duplicate column names

Duplicate column names are now supported in *`read_csv()`* whether they are in the file or passed in as the `names` parameter (GH7160, GH9424)

```
In [24]: data = "0,1,2\n3,4,5"

In [25]: names = ["a", "b", "a"]
```

Previous behavior:

```
In [2]: pd.read_csv(StringIO(data), names=names)
Out[2]:
   a  b  a
0  2  1  2
1  5  4  5
```

The first `a` column contained the same data as the second `a` column, when it should have contained the values `[0, 3]`.

New behavior:

```
In [26]: pd.read_csv(StringIO(data), names=names)
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-26-a095135d9435> in <module>
----> 1 pd.read_csv(StringIO(data), names=names)

/pandas/pandas/io/parsers.py in read_csv(filepath_or_buffer, sep, delimiter, header,␣
↪names, index_col, usecols, squeeze, prefix, mangle_dupe_cols, dtype, engine,␣
↪converters, true_values, false_values, skipinitialspace, skiprows, skipfooter,␣
↪nrows, na_values, keep_default_na, na_filter, verbose, skip_blank_lines, parse_
↪dates, infer_datetime_format, keep_date_col, date_parser, dayfirst, cache_dates,␣
↪iterator, chunksize, compression, thousands, decimal, lineterminator, quotechar,␣
↪quoting, doublequote, escapechar, comment, encoding, dialect, error_bad_lines, warn_
↪bad_lines, delim_whitespace, low_memory, memory_map, float_precision, storage_
↪options)
    608     kwds.update(kwds_defaults)
    609
--> 610     return _read(filepath_or_buffer, kwds)
    611
    612

/pandas/pandas/io/parsers.py in _read(filepath_or_buffer, kwds)
    457
    458     # Check for duplicates in names.
--> 459     _validate_names(kwds.get("names", None))
    460
    461     # Create the parser.

/pandas/pandas/io/parsers.py in _validate_names(names)
    438     if names is not None:
    439         if len(names) != len(set(names)):
--> 440             raise ValueError("Duplicate names are not allowed.")
    441         if not (
    442             is_list_like(names, allow_sets=False) or isinstance(names, abc.
↪KeysView)
```

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```
ValueError: Duplicate names are not allowed.
```

Method `read_csv` supports parsing `Categorical` directly

The *read_csv()* function now supports parsing a `Categorical` column when specified as a dtype (GH10153). Depending on the structure of the data, this can result in a faster parse time and lower memory usage compared to converting to `Categorical` after parsing. See the io *docs here*.

```
In [27]: data = """
   ....: col1,col2,col3
   ....: a,b,1
   ....: a,b,2
   ....: c,d,3
   ....: """
   ....:

In [28]: pd.read_csv(StringIO(data))
Out[28]:
  col1 col2  col3
0    a    b     1
1    a    b     2
2    c    d     3

[3 rows x 3 columns]

In [29]: pd.read_csv(StringIO(data)).dtypes
Out[29]:
col1    object
col2    object
col3     int64
Length: 3, dtype: object

In [30]: pd.read_csv(StringIO(data), dtype="category").dtypes
Out[30]:
col1    category
col2    category
col3    category
Length: 3, dtype: object
```

Individual columns can be parsed as a `Categorical` using a dict specification

```
In [31]: pd.read_csv(StringIO(data), dtype={"col1": "category"}).dtypes
Out[31]:
col1    category
col2      object
col3       int64
Length: 3, dtype: object
```

Note: The resulting categories will always be parsed as strings (object dtype). If the categories are numeric they can be converted using the *to_numeric()* function, or as appropriate, another converter such as *to_datetime()*.

```
In [32]: df = pd.read_csv(StringIO(data), dtype="category")
```

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```
In [33]: df.dtypes
Out[33]:
col1    category
col2    category
col3    category
Length: 3, dtype: object

In [34]: df["col3"]
Out[34]:
0    1
1    2
2    3
Name: col3, Length: 3, dtype: category
Categories (3, object): ['1', '2', '3']

In [35]: df["col3"].cat.categories = pd.to_numeric(df["col3"].cat.categories)

In [36]: df["col3"]
Out[36]:
0    1
1    2
2    3
Name: col3, Length: 3, dtype: category
Categories (3, int64): [1, 2, 3]
```

Categorical concatenation

- A function `union_categoricals()` has been added for combining categoricals, see *Unioning Categoricals* (GH13361, GH13763, GH13846, GH14173)

```
In [37]: from pandas.api.types import union_categoricals

In [38]: a = pd.Categorical(["b", "c"])

In [39]: b = pd.Categorical(["a", "b"])

In [40]: union_categoricals([a, b])
Out[40]:
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']
```

- `concat` and `append` now can concat `category` dtypes with different `categories` as `object` dtype (GH13524)

```
In [41]: s1 = pd.Series(["a", "b"], dtype="category")

In [42]: s2 = pd.Series(["b", "c"], dtype="category")
```

Previous behavior:

```
In [1]: pd.concat([s1, s2])
ValueError: incompatible categories in categorical concat
```

New behavior:

```
In [43]: pd.concat([s1, s2])
Out[43]:
0    a
1    b
0    b
1    c
Length: 4, dtype: object
```

Semi-month offsets

pandas has gained new frequency offsets, `SemiMonthEnd` ('SM') and `SemiMonthBegin` ('SMS'). These provide date offsets anchored (by default) to the 15th and end of month, and 15th and 1st of month respectively. (GH1543)

```
In [44]: from pandas.tseries.offsets import SemiMonthEnd, SemiMonthBegin
```

SemiMonthEnd:

```
In [45]: pd.Timestamp("2016-01-01") + SemiMonthEnd()
Out[45]: Timestamp('2016-01-15 00:00:00')

In [46]: pd.date_range("2015-01-01", freq="SM", periods=4)
Out[46]: DatetimeIndex(['2015-01-15', '2015-01-31', '2015-02-15', '2015-02-28'],␣
↪dtype='datetime64[ns]', freq='SM-15')
```

SemiMonthBegin:

```
In [47]: pd.Timestamp("2016-01-01") + SemiMonthBegin()
Out[47]: Timestamp('2016-01-15 00:00:00')

In [48]: pd.date_range("2015-01-01", freq="SMS", periods=4)
Out[48]: DatetimeIndex(['2015-01-01', '2015-01-15', '2015-02-01', '2015-02-15'],␣
↪dtype='datetime64[ns]', freq='SMS-15')
```

Using the anchoring suffix, you can also specify the day of month to use instead of the 15th.

```
In [49]: pd.date_range("2015-01-01", freq="SMS-16", periods=4)
Out[49]: DatetimeIndex(['2015-01-01', '2015-01-16', '2015-02-01', '2015-02-16'],␣
↪dtype='datetime64[ns]', freq='SMS-16')

In [50]: pd.date_range("2015-01-01", freq="SM-14", periods=4)
Out[50]: DatetimeIndex(['2015-01-14', '2015-01-31', '2015-02-14', '2015-02-28'],␣
↪dtype='datetime64[ns]', freq='SM-14')
```

New Index methods

The following methods and options are added to `Index`, to be more consistent with the `Series` and `DataFrame` API.

`Index` now supports the `.where()` function for same shape indexing (GH13170)

```
In [51]: idx = pd.Index(["a", "b", "c"])

In [52]: idx.where([True, False, True])
Out[52]: Index(['a', nan, 'c'], dtype='object')
```

`Index` now supports `.dropna()` to exclude missing values (GH6194)

```
In [53]: idx = pd.Index([1, 2, np.nan, 4])

In [54]: idx.dropna()
Out[54]: Float64Index([1.0, 2.0, 4.0], dtype='float64')
```

For `MultiIndex`, values are dropped if any level is missing by default. Specifying `how='all'` only drops values where all levels are missing.

```
In [55]: midx = pd.MultiIndex.from_arrays([[1, 2, np.nan, 4], [1, 2, np.nan, np.nan]])

In [56]: midx
Out[56]:
MultiIndex([(1.0, 1.0),
            (2.0, 2.0),
            (nan, nan),
            (4.0, nan)],
           )

In [57]: midx.dropna()
Out[57]:
MultiIndex([(1, 1),
            (2, 2)],
           )

In [58]: midx.dropna(how="all")
Out[58]:
MultiIndex([(1, 1.0),
            (2, 2.0),
            (4, nan)],
           )
```

`Index` now supports `.str.extractall()` which returns a `DataFrame`, see the *docs here* (GH10008, GH13156)

```
In [59]: idx = pd.Index(["a1a2", "b1", "c1"])

In [60]: idx.str.extractall(r"[ab](?P<digit>\d)")
Out[60]:
        digit
  match
0 0         1
  1         2
1 0         1

[3 rows x 1 columns]
```

`Index.astype()` now accepts an optional boolean argument `copy`, which allows optional copying if the requirements on dtype are satisfied (GH13209)

Google BigQuery enhancements

- The *read_gbq()* method has gained the `dialect` argument to allow users to specify whether to use BigQuery's legacy SQL or BigQuery's standard SQL. See the docs for more details (GH13615).
- The *to_gbq()* method now allows the DataFrame column order to differ from the destination table schema (GH11359).

Fine-grained NumPy errstate

Previous versions of pandas would permanently silence numpy's ufunc error handling when `pandas` was imported. pandas did this in order to silence the warnings that would arise from using numpy ufuncs on missing data, which are usually represented as `NaN` s. Unfortunately, this silenced legitimate warnings arising in non-pandas code in the application. Starting with 0.19.0, pandas will use the `numpy.errstate` context manager to silence these warnings in a more fine-grained manner, only around where these operations are actually used in the pandas code base. (GH13109, GH13145)

After upgrading pandas, you may see *new* `RuntimeWarnings` being issued from your code. These are likely legitimate, and the underlying cause likely existed in the code when using previous versions of pandas that simply silenced the warning. Use numpy.errstate around the source of the `RuntimeWarning` to control how these conditions are handled.

Method `get_dummies` now returns integer dtypes

The `pd.get_dummies` function now returns dummy-encoded columns as small integers, rather than floats (GH8725). This should provide an improved memory footprint.

Previous behavior:

```
In [1]: pd.get_dummies(['a', 'b', 'a', 'c']).dtypes

Out[1]:
a    float64
b    float64
c    float64
dtype: object
```

New behavior:

```
In [61]: pd.get_dummies(["a", "b", "a", "c"]).dtypes
Out[61]:
a    uint8
b    uint8
c    uint8
Length: 3, dtype: object
```

Downcast values to smallest possible dtype in `to_numeric`

`pd.to_numeric()` now accepts a `downcast` parameter, which will downcast the data if possible to smallest specified numerical dtype (GH13352)

```
In [62]: s = ["1", 2, 3]

In [63]: pd.to_numeric(s, downcast="unsigned")
Out[63]: array([1, 2, 3], dtype=uint8)

In [64]: pd.to_numeric(s, downcast="integer")
Out[64]: array([1, 2, 3], dtype=int8)
```

pandas development API

As part of making pandas API more uniform and accessible in the future, we have created a standard sub-package of pandas, `pandas.api` to hold public API's. We are starting by exposing type introspection functions in `pandas.api.types`. More sub-packages and officially sanctioned API's will be published in future versions of pandas (GH13147, GH13634)

The following are now part of this API:

```
In [65]: import pprint

In [66]: from pandas.api import types

In [67]: funcs = [f for f in dir(types) if not f.startswith("_")]

In [68]: pprint.pprint(funcs)
['CategoricalDtype',
 'DatetimeTZDtype',
 'IntervalDtype',
 'PeriodDtype',
 'infer_dtype',
 'is_array_like',
 'is_bool',
 'is_bool_dtype',
 'is_categorical',
 'is_categorical_dtype',
 'is_complex',
 'is_complex_dtype',
 'is_datetime64_any_dtype',
 'is_datetime64_dtype',
 'is_datetime64_ns_dtype',
 'is_datetime64tz_dtype',
 'is_dict_like',
 'is_dtype_equal',
 'is_extension_array_dtype',
 'is_extension_type',
 'is_file_like',
 'is_float',
 'is_float_dtype',
 'is_hashable',
 'is_int64_dtype',
 'is_integer',
 'is_integer_dtype',
```

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```
'is_interval',
'is_interval_dtype',
'is_iterator',
'is_list_like',
'is_named_tuple',
'is_number',
'is_numeric_dtype',
'is_object_dtype',
'is_period_dtype',
'is_re',
'is_re_compilable',
'is_scalar',
'is_signed_integer_dtype',
'is_sparse',
'is_string_dtype',
'is_timedelta64_dtype',
'is_timedelta64_ns_dtype',
'is_unsigned_integer_dtype',
'pandas_dtype',
'union_categoricals']
```

Note: Calling these functions from the internal module `pandas.core.common` will now show a `DeprecationWarning` (GH13990)

Other enhancements

- `Timestamp` can now accept positional and keyword parameters similar to `datetime.datetime()` (GH10758, GH11630)

```
In [69]: pd.Timestamp(2012, 1, 1)
Out[69]: Timestamp('2012-01-01 00:00:00')

In [70]: pd.Timestamp(year=2012, month=1, day=1, hour=8, minute=30)
Out[70]: Timestamp('2012-01-01 08:30:00')
```

- The `.resample()` function now accepts a `on=` or `level=` parameter for resampling on a datetimelike column or `MultiIndex` level (GH13500)

```
In [71]: df = pd.DataFrame(
   ....:     {"date": pd.date_range("2015-01-01", freq="W", periods=5), "a": np.
↪arange(5)},
   ....:     index=pd.MultiIndex.from_arrays(
   ....:         [[1, 2, 3, 4, 5], pd.date_range("2015-01-01", freq="W",␣
↪periods=5)],
   ....:         names=["v", "d"],
   ....:     ),
   ....: )
   ....:

In [72]: df
Out[72]:
                  date  a
v d
```

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```
1 2015-01-04 2015-01-04  0
2 2015-01-11 2015-01-11  1
3 2015-01-18 2015-01-18  2
4 2015-01-25 2015-01-25  3
5 2015-02-01 2015-02-01  4

[5 rows x 2 columns]

In [73]: df.resample("M", on="date").sum()
Out[73]:
            a
date
2015-01-31  6
2015-02-28  4

[2 rows x 1 columns]

In [74]: df.resample("M", level="d").sum()
Out[74]:
            a
d
2015-01-31  6
2015-02-28  4

[2 rows x 1 columns]
```

- The `.get_credentials()` method of `GbqConnector` can now first try to fetch the application default credentials. See the docs for more details (GH13577).
- The `.tz_localize()` method of `DatetimeIndex` and `Timestamp` has gained the `errors` keyword, so you can potentially coerce nonexistent timestamps to `NaT`. The default behavior remains to raising a `NonExistentTimeError` (GH13057)
- `.to_hdf/read_hdf()` now accept path objects (e.g. `pathlib.Path`, `py.path.local`) for the file path (GH11773)
- The `pd.read_csv()` with `engine='python'` has gained support for the `decimal` (GH12933), `na_filter` (GH13321) and the `memory_map` option (GH13381).
- Consistent with the Python API, `pd.read_csv()` will now interpret `+inf` as positive infinity (GH13274)
- The `pd.read_html()` has gained support for the `na_values`, `converters`, `keep_default_na` options (GH13461)
- `Categorical.astype()` now accepts an optional boolean argument `copy`, effective when dtype is categorical (GH13209)
- `DataFrame` has gained the `.asof()` method to return the last non-NaN values according to the selected subset (GH13358)
- The `DataFrame` constructor will now respect key ordering if a list of `OrderedDict` objects are passed in (GH13304)
- `pd.read_html()` has gained support for the `decimal` option (GH12907)
- `Series` has gained the properties `.is_monotonic`, `.is_monotonic_increasing`, `.is_monotonic_decreasing`, similar to `Index` (GH13336)
- `DataFrame.to_sql()` now allows a single value as the SQL type for all columns (GH11886).
- `Series.append` now supports the `ignore_index` option (GH13677)

- `.to_stata()` and `StataWriter` can now write variable labels to Stata dta files using a dictionary to make column names to labels (GH13535, GH13536)
- `.to_stata()` and `StataWriter` will automatically convert `datetime64[ns]` columns to Stata format `%tc`, rather than raising a `ValueError` (GH12259)
- `read_stata()` and `StataReader` raise with a more explicit error message when reading Stata files with repeated value labels when `convert_categoricals=True` (GH13923)
- `DataFrame.style` will now render sparsified MultiIndexes (GH11655)
- `DataFrame.style` will now show column level names (e.g. `DataFrame.columns.names`) (GH13775)
- `DataFrame` has gained support to re-order the columns based on the values in a row using `df.sort_values(by='...', axis=1)` (GH10806)

```
In [75]: df = pd.DataFrame({"A": [2, 7], "B": [3, 5], "C": [4, 8]}, index=["row1",
↪ "row2"])

In [76]: df
Out[76]:
      A  B  C
row1  2  3  4
row2  7  5  8

[2 rows x 3 columns]

In [77]: df.sort_values(by="row2", axis=1)
Out[77]:
      B  A  C
row1  3  2  4
row2  5  7  8

[2 rows x 3 columns]
```

- Added documentation to *I/O* regarding the perils of reading in columns with mixed dtypes and how to handle it (GH13746)
- *`to_html()`* now has a `border` argument to control the value in the opening `<table>` tag. The default is the value of the `html.border` option, which defaults to 1. This also affects the notebook HTML repr, but since Jupyter's CSS includes a border-width attribute, the visual effect is the same. (GH11563).
- Raise `ImportError` in the sql functions when `sqlalchemy` is not installed and a connection string is used (GH11920).
- Compatibility with matplotlib 2.0. Older versions of pandas should also work with matplotlib 2.0 (GH13333)
- `Timestamp`, `Period`, `DatetimeIndex`, `PeriodIndex` and `.dt` accessor have gained a `.is_leap_year` property to check whether the date belongs to a leap year. (GH13727)
- `astype()` will now accept a dict of column name to data types mapping as the `dtype` argument. (GH12086)
- The `pd.read_json` and `DataFrame.to_json` has gained support for reading and writing json lines with `lines` option see *Line delimited json* (GH9180)
- *`read_excel()`* now supports the true_values and false_values keyword arguments (GH13347)
- `groupby()` will now accept a scalar and a single-element list for specifying `level` on a non-`MultiIndex` grouper. (GH13907)
- Non-convertible dates in an excel date column will be returned without conversion and the column will be `object` dtype, rather than raising an exception (GH10001).

- `pd.Timedelta(None)` is now accepted and will return `NaT`, mirroring `pd.Timestamp` (GH13687)
- `pd.read_stata()` can now handle some format 111 files, which are produced by SAS when generating Stata dta files (GH11526)
- `Series` and `Index` now support `divmod` which will return a tuple of series or indices. This behaves like a standard binary operator with regards to broadcasting rules (GH14208).

API changes

`Series.tolist()` will now return Python types

`Series.tolist()` will now return Python types in the output, mimicking NumPy `.tolist()` behavior (GH10904)

```
In [78]: s = pd.Series([1, 2, 3])
```

Previous behavior:

```
In [7]: type(s.tolist()[0])
Out[7]:
 <class 'numpy.int64'>
```

New behavior:

```
In [79]: type(s.tolist()[0])
Out[79]: int
```

`Series` operators for different indexes

Following `Series` operators have been changed to make all operators consistent, including `DataFrame` (GH1134, GH4581, GH13538)

- `Series` comparison operators now raise `ValueError` when `index` are different.
- `Series` logical operators align both `index` of left and right hand side.

Warning: Until 0.18.1, comparing `Series` with the same length, would succeed even if the `.index` are different (the result ignores `.index`). As of 0.19.0, this will raises `ValueError` to be more strict. This section also describes how to keep previous behavior or align different indexes, using the flexible comparison methods like `.eq`.

As a result, `Series` and `DataFrame` operators behave as below:

Arithmetic operators

Arithmetic operators align both `index` (no changes).

```
In [80]: s1 = pd.Series([1, 2, 3], index=list("ABC"))

In [81]: s2 = pd.Series([2, 2, 2], index=list("ABD"))

In [82]: s1 + s2
Out[82]:
A    3.0
B    4.0
C    NaN
D    NaN
Length: 4, dtype: float64

In [83]: df1 = pd.DataFrame([1, 2, 3], index=list("ABC"))

In [84]: df2 = pd.DataFrame([2, 2, 2], index=list("ABD"))

In [85]: df1 + df2
Out[85]:
     0
A  3.0
B  4.0
C  NaN
D  NaN

[4 rows x 1 columns]
```

Comparison operators

Comparison operators raise `ValueError` when `.index` are different.

Previous behavior (`Series`):

`Series` compared values ignoring the `.index` as long as both had the same length:

```
In [1]: s1 == s2
Out[1]:
A    False
B     True
C    False
dtype: bool
```

New behavior (`Series`):

```
In [2]: s1 == s2
Out[2]:
ValueError: Can only compare identically-labeled Series objects
```

Note: To achieve the same result as previous versions (compare values based on locations ignoring `.index`), compare both `.values`.

```
In [86]: s1.values == s2.values
Out[86]: array([False,  True, False])
```

If you want to compare `Series` aligning its `.index`, see flexible comparison methods section below:

```
In [87]: s1.eq(s2)
Out[87]:
A    False
B     True
C    False
D    False
Length: 4, dtype: bool
```

Current behavior (`DataFrame`, no change):

```
In [3]: df1 == df2
Out[3]:
ValueError: Can only compare identically-labeled DataFrame objects
```

Logical operators

Logical operators align both `.index` of left and right hand side.

Previous behavior (`Series`), only left hand side `index` was kept:

```
In [4]: s1 = pd.Series([True, False, True], index=list('ABC'))
In [5]: s2 = pd.Series([True, True, True], index=list('ABD'))
In [6]: s1 & s2
Out[6]:
A     True
B    False
C    False
dtype: bool
```

New behavior (`Series`):

```
In [88]: s1 = pd.Series([True, False, True], index=list("ABC"))

In [89]: s2 = pd.Series([True, True, True], index=list("ABD"))

In [90]: s1 & s2
Out[90]:
A     True
B    False
C    False
D    False
Length: 4, dtype: bool
```

Note: `Series` logical operators fill a `NaN` result with `False`.

Note: To achieve the same result as previous versions (compare values based on only left hand side index), you can use `reindex_like`:

```
In [91]: s1 & s2.reindex_like(s1)
Out[91]:
```

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```
A     True
B    False
C    False
Length: 3, dtype: bool
```

Current behavior (`DataFrame`, no change):

```
In [92]: df1 = pd.DataFrame([True, False, True], index=list("ABC"))

In [93]: df2 = pd.DataFrame([True, True, True], index=list("ABD"))

In [94]: df1 & df2
Out[94]:
       0
A   True
B  False
C  False
D  False

[4 rows x 1 columns]
```

Flexible comparison methods

`Series` flexible comparison methods like `eq`, `ne`, `le`, `lt`, `ge` and `gt` now align both `index`. Use these operators if you want to compare two `Series` which has the different `index`.

```
In [95]: s1 = pd.Series([1, 2, 3], index=["a", "b", "c"])

In [96]: s2 = pd.Series([2, 2, 2], index=["b", "c", "d"])

In [97]: s1.eq(s2)
Out[97]:
a    False
b     True
c    False
d    False
Length: 4, dtype: bool

In [98]: s1.ge(s2)
Out[98]:
a    False
b     True
c     True
d    False
Length: 4, dtype: bool
```

Previously, this worked the same as comparison operators (see above).

`Series` type promotion on assignment

A `Series` will now correctly promote its dtype for assignment with incompat values to the current dtype (GH13234)

```
In [99]: s = pd.Series()
```

Previous behavior:

```
In [2]: s["a"] = pd.Timestamp("2016-01-01")

In [3]: s["b"] = 3.0
TypeError: invalid type promotion
```

New behavior:

```
In [100]: s["a"] = pd.Timestamp("2016-01-01")

In [101]: s["b"] = 3.0

In [102]: s
Out[102]:
a    2016-01-01 00:00:00
b                    3.0
Length: 2, dtype: object

In [103]: s.dtype
Out[103]: dtype('O')
```

Function `.to_datetime()` changes

Previously if `.to_datetime()` encountered mixed integers/floats and strings, but no datetimes with `errors='coerce'` it would convert all to `NaT`.

Previous behavior:

```
In [2]: pd.to_datetime([1, 'foo'], errors='coerce')
Out[2]: DatetimeIndex(['NaT', 'NaT'], dtype='datetime64[ns]', freq=None)
```

Current behavior:

This will now convert integers/floats with the default unit of `ns`.

```
In [104]: pd.to_datetime([1, "foo"], errors="coerce")
Out[104]: DatetimeIndex(['1970-01-01 00:00:00.000000001', 'NaT'], dtype=
↪'datetime64[ns]', freq=None)
```

Bug fixes related to `.to_datetime()`:

- Bug in `pd.to_datetime()` when passing integers or floats, and no `unit` and `errors='coerce'` (GH13180).
- Bug in `pd.to_datetime()` when passing invalid data types (e.g. bool); will now respect the `errors` keyword (GH13176)
- Bug in `pd.to_datetime()` which overflowed on `int8`, and `int16` dtypes (GH13451)
- Bug in `pd.to_datetime()` raise `AttributeError` with `NaN` and the other string is not valid when `errors='ignore'` (GH12424)

- Bug in `pd.to_datetime()` did not cast floats correctly when `unit` was specified, resulting in truncated datetime (GH13834)

Merging changes

Merging will now preserve the dtype of the join keys (GH8596)

```
In [105]: df1 = pd.DataFrame({"key": [1], "v1": [10]})

In [106]: df1
Out[106]:
   key  v1
0    1  10

[1 rows x 2 columns]

In [107]: df2 = pd.DataFrame({"key": [1, 2], "v1": [20, 30]})

In [108]: df2
Out[108]:
   key  v1
0    1  20
1    2  30

[2 rows x 2 columns]
```

Previous behavior:

```
In [5]: pd.merge(df1, df2, how='outer')
Out[5]:
   key    v1
0  1.0  10.0
1  1.0  20.0
2  2.0  30.0

In [6]: pd.merge(df1, df2, how='outer').dtypes
Out[6]:
key    float64
v1     float64
dtype: object
```

New behavior:

We are able to preserve the join keys

```
In [109]: pd.merge(df1, df2, how="outer")
Out[109]:
   key  v1
0    1  10
1    1  20
2    2  30

[3 rows x 2 columns]

In [110]: pd.merge(df1, df2, how="outer").dtypes
Out[110]:
key    int64
```

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```
v1     int64
Length: 2, dtype: object
```

Of course if you have missing values that are introduced, then the resulting dtype will be upcast, which is unchanged from previous.

```
In [111]: pd.merge(df1, df2, how="outer", on="key")
Out[111]:
   key  v1_x  v1_y
0    1  10.0    20
1    2   NaN    30

[2 rows x 3 columns]

In [112]: pd.merge(df1, df2, how="outer", on="key").dtypes
Out[112]:
key       int64
v1_x    float64
v1_y      int64
Length: 3, dtype: object
```

Method `.describe()` changes

Percentile identifiers in the index of a `.describe()` output will now be rounded to the least precision that keeps them distinct (GH13104)

```
In [113]: s = pd.Series([0, 1, 2, 3, 4])

In [114]: df = pd.DataFrame([0, 1, 2, 3, 4])
```

Previous behavior:

The percentiles were rounded to at most one decimal place, which could raise `ValueError` for a data frame if the percentiles were duplicated.

```
In [3]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[3]:
count     5.000000
mean      2.000000
std       1.581139
min       0.000000
0.0%      0.000400
0.1%      0.002000
0.1%      0.004000
50%       2.000000
99.9%     3.996000
100.0%    3.998000
100.0%    3.999600
max       4.000000
dtype: float64

In [4]: df.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[4]:
...
ValueError: cannot reindex from a duplicate axis
```

New behavior:

```
In [115]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[115]:
count     5.000000
mean      2.000000
std       1.581139
min       0.000000
0.01%     0.000400
0.05%     0.002000
0.1%      0.004000
50%       2.000000
99.9%     3.996000
99.95%    3.998000
99.99%    3.999600
max       4.000000
Length: 12, dtype: float64

In [116]: df.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[116]:
                0
count    5.000000
mean     2.000000
std      1.581139
min      0.000000
0.01%    0.000400
0.05%    0.002000
0.1%     0.004000
50%      2.000000
99.9%    3.996000
99.95%   3.998000
99.99%   3.999600
max      4.000000

[12 rows x 1 columns]
```

Furthermore:

- Passing duplicated `percentiles` will now raise a `ValueError`.
- Bug in `.describe()` on a DataFrame with a mixed-dtype column index, which would previously raise a `TypeError` (GH13288)

`Period` changes

The `PeriodIndex` now has `period` dtype

`PeriodIndex` now has its own `period` dtype. The `period` dtype is a pandas extension dtype like `category` or the *timezone aware dtype* (`datetime64[ns, tz]`) (GH13941). As a consequence of this change, `PeriodIndex` no longer has an integer dtype:

Previous behavior:

```
In [1]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')

In [2]: pi
Out[2]: PeriodIndex(['2016-08-01'], dtype='int64', freq='D')
```

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```
In [3]: pd.api.types.is_integer_dtype(pi)
Out[3]: True

In [4]: pi.dtype
Out[4]: dtype('int64')
```

New behavior:

```
In [117]: pi = pd.PeriodIndex(["2016-08-01"], freq="D")

In [118]: pi
Out[118]: PeriodIndex(['2016-08-01'], dtype='period[D]', freq='D')

In [119]: pd.api.types.is_integer_dtype(pi)
Out[119]: False

In [120]: pd.api.types.is_period_dtype(pi)
Out[120]: True

In [121]: pi.dtype
Out[121]: period[D]

In [122]: type(pi.dtype)
Out[122]: pandas.core.dtypes.dtypes.PeriodDtype
```

`Period('NaT')` now returns `pd.NaT`

Previously, `Period` has its own `Period('NaT')` representation different from `pd.NaT`. Now `Period('NaT')` has been changed to return `pd.NaT`. (GH12759, GH13582)

Previous behavior:

```
In [5]: pd.Period('NaT', freq='D')
Out[5]: Period('NaT', 'D')
```

New behavior:

These result in `pd.NaT` without providing `freq` option.

```
In [123]: pd.Period("NaT")
Out[123]: NaT

In [124]: pd.Period(None)
Out[124]: NaT
```

To be compatible with `Period` addition and subtraction, `pd.NaT` now supports addition and subtraction with `int`. Previously it raised `ValueError`.

Previous behavior:

```
In [5]: pd.NaT + 1
...
ValueError: Cannot add integral value to Timestamp without freq.
```

New behavior:

```
In [125]: pd.NaT + 1
Out[125]: NaT

In [126]: pd.NaT - 1
Out[126]: NaT
```

`PeriodIndex.values` now returns array of `Period` object

`.values` is changed to return an array of `Period` objects, rather than an array of integers (GH13988).

Previous behavior:

```
In [6]: pi = pd.PeriodIndex(['2011-01', '2011-02'], freq='M')
In [7]: pi.values
Out[7]: array([492, 493])
```

New behavior:

```
In [127]: pi = pd.PeriodIndex(["2011-01", "2011-02"], freq="M")

In [128]: pi.values
Out[128]: array([Period('2011-01', 'M'), Period('2011-02', 'M')], dtype=object)
```

Index + / - no longer used for set operations

Addition and subtraction of the base Index type and of DatetimeIndex (not the numeric index types) previously performed set operations (set union and difference). This behavior was already deprecated since 0.15.0 (in favor using the specific `.union()` and `.difference()` methods), and is now disabled. When possible, + and - are now used for element-wise operations, for example for concatenating strings or subtracting datetimes (GH8227, GH14127).

Previous behavior:

```
In [1]: pd.Index(['a', 'b']) + pd.Index(['a', 'c'])
FutureWarning: using '+' to provide set union with Indexes is deprecated, use '|' or .
↪union()
Out[1]: Index(['a', 'b', 'c'], dtype='object')
```

New behavior: the same operation will now perform element-wise addition:

```
In [129]: pd.Index(["a", "b"]) + pd.Index(["a", "c"])
Out[129]: Index(['aa', 'bc'], dtype='object')
```

Note that numeric Index objects already performed element-wise operations. For example, the behavior of adding two integer Indexes is unchanged. The base `Index` is now made consistent with this behavior.

```
In [130]: pd.Index([1, 2, 3]) + pd.Index([2, 3, 4])
Out[130]: Int64Index([3, 5, 7], dtype='int64')
```

Further, because of this change, it is now possible to subtract two DatetimeIndex objects resulting in a TimedeltaIndex:

Previous behavior:

```
In [1]: (pd.DatetimeIndex(['2016-01-01', '2016-01-02'])
   ...:  - pd.DatetimeIndex(['2016-01-02', '2016-01-03']))
FutureWarning: using '-' to provide set differences with datetimelike Indexes is␣
↪deprecated, use .difference()
Out[1]: DatetimeIndex(['2016-01-01'], dtype='datetime64[ns]', freq=None)
```

New behavior:

```
In [131]: (
   .....:     pd.DatetimeIndex(["2016-01-01", "2016-01-02"])
   .....:     - pd.DatetimeIndex(["2016-01-02", "2016-01-03"])
   .....: )
   .....:
Out[131]: TimedeltaIndex(['-1 days', '-1 days'], dtype='timedelta64[ns]', freq=None)
```

`Index.difference` and `.symmetric_difference` changes

`Index.difference` and `Index.symmetric_difference` will now, more consistently, treat `NaN` values as any other values. (GH13514)

```
In [132]: idx1 = pd.Index([1, 2, 3, np.nan])

In [133]: idx2 = pd.Index([0, 1, np.nan])
```

Previous behavior:

```
In [3]: idx1.difference(idx2)
Out[3]: Float64Index([nan, 2.0, 3.0], dtype='float64')

In [4]: idx1.symmetric_difference(idx2)
Out[4]: Float64Index([0.0, nan, 2.0, 3.0], dtype='float64')
```

New behavior:

```
In [134]: idx1.difference(idx2)
Out[134]: Float64Index([2.0, 3.0], dtype='float64')

In [135]: idx1.symmetric_difference(idx2)
Out[135]: Float64Index([0.0, 2.0, 3.0], dtype='float64')
```

`Index.unique` consistently returns `Index`

`Index.unique()` now returns unique values as an `Index` of the appropriate `dtype`. (GH13395). Previously, most `Index` classes returned `np.ndarray`, and `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex` returned `Index` to keep metadata like timezone.

Previous behavior:

```
In [1]: pd.Index([1, 2, 3]).unique()
Out[1]: array([1, 2, 3])

In [2]: pd.DatetimeIndex(['2011-01-01', '2011-01-02',
   ...:                   '2011-01-03'], tz='Asia/Tokyo').unique()
Out[2]:
```

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```
DatetimeIndex(['2011-01-01 00:00:00+09:00', '2011-01-02 00:00:00+09:00',
               '2011-01-03 00:00:00+09:00'],
              dtype='datetime64[ns, Asia/Tokyo]', freq=None)
```

New behavior:

```
In [136]: pd.Index([1, 2, 3]).unique()
Out[136]: Int64Index([1, 2, 3], dtype='int64')

In [137]: pd.DatetimeIndex(
   .....:     ["2011-01-01", "2011-01-02", "2011-01-03"], tz="Asia/Tokyo"
   .....: ).unique()
   .....:
Out[137]:
DatetimeIndex(['2011-01-01 00:00:00+09:00', '2011-01-02 00:00:00+09:00',
               '2011-01-03 00:00:00+09:00'],
              dtype='datetime64[ns, Asia/Tokyo]', freq=None)
```

`MultiIndex` constructors, `groupby` and `set_index` preserve categorical dtypes

`MultiIndex.from_arrays` and `MultiIndex.from_product` will now preserve categorical dtype in `MultiIndex` levels (GH13743, GH13854).

```
In [138]: cat = pd.Categorical(["a", "b"], categories=list("bac"))

In [139]: lvl1 = ["foo", "bar"]

In [140]: midx = pd.MultiIndex.from_arrays([cat, lvl1])

In [141]: midx
Out[141]:
MultiIndex([('a', 'foo'),
            ('b', 'bar')],
           )
```

Previous behavior:

```
In [4]: midx.levels[0]
Out[4]: Index(['b', 'a', 'c'], dtype='object')

In [5]: midx.get_level_values[0]
Out[5]: Index(['a', 'b'], dtype='object')
```

New behavior: the single level is now a `CategoricalIndex`:

```
In [142]: midx.levels[0]
Out[142]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
↪ dtype='category')

In [143]: midx.get_level_values(0)
Out[143]: CategoricalIndex(['a', 'b'], categories=['b', 'a', 'c'], ordered=False,␣
↪dtype='category')
```

An analogous change has been made to `MultiIndex.from_product`. As a consequence, `groupby` and `set_index` also preserve categorical dtypes in indexes

```
In [144]: df = pd.DataFrame({"A": [0, 1], "B": [10, 11], "C": cat})

In [145]: df_grouped = df.groupby(by=["A", "C"]).first()

In [146]: df_set_idx = df.set_index(["A", "C"])
```

Previous behavior:

```
In [11]: df_grouped.index.levels[1]
Out[11]: Index(['b', 'a', 'c'], dtype='object', name='C')
In [12]: df_grouped.reset_index().dtypes
Out[12]:
A      int64
C     object
B    float64
dtype: object

In [13]: df_set_idx.index.levels[1]
Out[13]: Index(['b', 'a', 'c'], dtype='object', name='C')
In [14]: df_set_idx.reset_index().dtypes
Out[14]:
A      int64
C     object
B      int64
dtype: object
```

New behavior:

```
In [147]: df_grouped.index.levels[1]
Out[147]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
↪ name='C', dtype='category')

In [148]: df_grouped.reset_index().dtypes
Out[148]:
A       int64
C    category
B     float64
Length: 3, dtype: object

In [149]: df_set_idx.index.levels[1]
Out[149]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
↪ name='C', dtype='category')

In [150]: df_set_idx.reset_index().dtypes
Out[150]:
A       int64
C    category
B       int64
Length: 3, dtype: object
```

Function `read_csv` will progressively enumerate chunks

When *`read_csv()`* is called with `chunksize=n` and without specifying an index, each chunk used to have an independently generated index from `0` to `n-1`. They are now given instead a progressive index, starting from `0` for the first chunk, from `n` for the second, and so on, so that, when concatenated, they are identical to the result of calling *`read_csv()`* without the `chunksize=` argument (GH12185).

```
In [151]: data = "A,B\n0,1\n2,3\n4,5\n6,7"
```

Previous behavior:

```
In [2]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
Out[2]:
   A  B
0  0  1
1  2  3
0  4  5
1  6  7
```

New behavior:

```
In [152]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
Out[152]:
   A  B
0  0  1
1  2  3
2  4  5
3  6  7

[4 rows x 2 columns]
```

Sparse changes

These changes allow pandas to handle sparse data with more dtypes, and for work to make a smoother experience with data handling.

Types `int64` and `bool` support enhancements

Sparse data structures now gained enhanced support of `int64` and `bool dtype` (GH667, GH13849).

Previously, sparse data were `float64` dtype by default, even if all inputs were of `int` or `bool` dtype. You had to specify `dtype` explicitly to create sparse data with `int64` dtype. Also, `fill_value` had to be specified explicitly because the default was `np.nan` which doesn't appear in `int64` or `bool` data.

```
In [1]: pd.SparseArray([1, 2, 0, 0])
Out[1]:
[1.0, 2.0, 0.0, 0.0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

# specifying int64 dtype, but all values are stored in sp_values because
# fill_value default is np.nan
In [2]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
```

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```
Out[2]:
[1, 2, 0, 0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

In [3]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64, fill_value=0)
Out[3]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)
```

As of v0.19.0, sparse data keeps the input dtype, and uses more appropriate `fill_value` defaults (`0` for `int64` dtype, `False` for `bool` dtype).

```
In [153]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
Out[153]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)

In [154]: pd.SparseArray([True, False, False, False])
Out[154]:
[True, False, False, False]
Fill: False
IntIndex
Indices: array([0], dtype=int32)
```

See the *docs* for more details.

Operators now preserve dtypes

- Sparse data structure now can preserve `dtype` after arithmetic ops (GH13848)

```
s = pd.SparseSeries([0, 2, 0, 1], fill_value=0, dtype=np.int64)
s.dtype

s + 1
```

- Sparse data structure now support `astype` to convert internal `dtype` (GH13900)

```
s = pd.SparseSeries([1.0, 0.0, 2.0, 0.0], fill_value=0)
s
s.astype(np.int64)
```

`astype` fails if data contains values which cannot be converted to specified `dtype`. Note that the limitation is applied to `fill_value` which default is `np.nan`.

```
In [7]: pd.SparseSeries([1., np.nan, 2., np.nan], fill_value=np.nan).astype(np.int64)
Out[7]:
ValueError: unable to coerce current fill_value nan to int64 dtype
```

Other sparse fixes

- Subclassed `SparseDataFrame` and `SparseSeries` now preserve class types when slicing or transposing. (GH13787)
- `SparseArray` with `bool` dtype now supports logical (bool) operators (GH14000)
- Bug in `SparseSeries` with `MultiIndex []` indexing may raise `IndexError` (GH13144)
- Bug in `SparseSeries` with `MultiIndex []` indexing result may have normal `Index` (GH13144)
- Bug in `SparseDataFrame` in which `axis=None` did not default to `axis=0` (GH13048)
- Bug in `SparseSeries` and `SparseDataFrame` creation with `object` dtype may raise `TypeError` (GH11633)
- Bug in `SparseDataFrame` doesn't respect passed `SparseArray` or `SparseSeries` 's dtype and `fill_value` (GH13866)
- Bug in `SparseArray` and `SparseSeries` don't apply ufunc to `fill_value` (GH13853)
- Bug in `SparseSeries.abs` incorrectly keeps negative `fill_value` (GH13853)
- Bug in single row slicing on multi-type `SparseDataFrame` s, types were previously forced to float (GH13917)
- Bug in `SparseSeries` slicing changes integer dtype to float (GH8292)
- Bug in `SparseDataFarme` comparison ops may raise `TypeError` (GH13001)
- Bug in `SparseDataFarme.isnull` raises `ValueError` (GH8276)
- Bug in `SparseSeries` representation with `bool` dtype may raise `IndexError` (GH13110)
- Bug in `SparseSeries` and `SparseDataFrame` of `bool` or `int64` dtype may display its values like `float64` dtype (GH13110)
- Bug in sparse indexing using `SparseArray` with `bool` dtype may return incorrect result (GH13985)
- Bug in `SparseArray` created from `SparseSeries` may lose `dtype` (GH13999)
- Bug in `SparseSeries` comparison with dense returns normal `Series` rather than `SparseSeries` (GH13999)

Indexer dtype changes

Note: This change only affects 64 bit python running on Windows, and only affects relatively advanced indexing operations

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Methods such as `Index.get_indexer` that return an indexer array, coerce that array to a "platform int", so that it can be directly used in 3rd party library operations like `numpy.take`. Previously, a platform int was defined as `np.int_` which corresponds to a C integer, but the correct type, and what is being used now, is `np.intp`, which corresponds to the C integer size that can hold a pointer (GH3033, GH13972).

These types are the same on many platform, but for 64 bit python on Windows, `np.int_` is 32 bits, and `np.intp` is 64 bits. Changing this behavior improves performance for many operations on that platform.

Previous behavior:

```
In [1]: i = pd.Index(['a', 'b', 'c'])

In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int32')
```

New behavior:

```
In [1]: i = pd.Index(['a', 'b', 'c'])

In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int64')
```

Other API changes

- `Timestamp.to_pydatetime` will issue a `UserWarning` when `warn=True`, and the instance has a non-zero number of nanoseconds, previously this would print a message to stdout (GH14101).
- `Series.unique()` with datetime and timezone now returns return array of `Timestamp` with timezone (GH13565).
- `Panel.to_sparse()` will raise a `NotImplementedError` exception when called (GH13778).
- `Index.reshape()` will raise a `NotImplementedError` exception when called (GH12882).
- `.filter()` enforces mutual exclusion of the keyword arguments (GH12399).
- `eval`'s upcasting rules for `float32` types have been updated to be more consistent with NumPy's rules. New behavior will not upcast to `float64` if you multiply a pandas `float32` object by a scalar float64 (GH12388).
- An `UnsupportedFunctionCall` error is now raised if NumPy ufuncs like `np.mean` are called on groupby or resample objects (GH12811).
- `__setitem__` will no longer apply a callable rhs as a function instead of storing it. Call `where` directly to get the previous behavior (GH13299).
- Calls to `.sample()` will respect the random seed set via `numpy.random.seed(n)` (GH13161)
- `Styler.apply` is now more strict about the outputs your function must return. For `axis=0` or `axis=1`, the output shape must be identical. For `axis=None`, the output must be a DataFrame with identical columns and index labels (GH13222).
- `Float64Index.astype(int)` will now raise `ValueError` if `Float64Index` contains `NaN` values (GH13149)
- `TimedeltaIndex.astype(int)` and `DatetimeIndex.astype(int)` will now return `Int64Index` instead of `np.array` (GH13209)
- Passing `Period` with multiple frequencies to normal `Index` now returns `Index` with `object` dtype (GH13664)
- `PeriodIndex.fillna` with `Period` has different freq now coerces to `object` dtype (GH13664)
- Faceted boxplots from `DataFrame.boxplot(by=col)` now return a `Series` when `return_type` is not None. Previously these returned an `OrderedDict`. Note that when `return_type=None`, the default, these still return a 2-D NumPy array (GH12216, GH7096).
- `pd.read_hdf` will now raise a `ValueError` instead of `KeyError`, if a mode other than `r`, `r+` and `a` is supplied. (GH13623)

- `pd.read_csv()`, `pd.read_table()`, and `pd.read_hdf()` raise the builtin `FileNotFoundError` exception for Python 3.x when called on a nonexistent file; this is back-ported as `IOError` in Python 2.x (GH14086)
- More informative exceptions are passed through the csv parser. The exception type would now be the original exception type instead of `CParserError` (GH13652).
- `pd.read_csv()` in the C engine will now issue a `ParserWarning` or raise a `ValueError` when `sep` encoded is more than one character long (GH14065)
- `DataFrame.values` will now return `float64` with a `DataFrame` of mixed `int64` and `uint64` dtypes, conforming to `np.find_common_type` (GH10364, GH13917)
- `.groupby.groups` will now return a dictionary of `Index` objects, rather than a dictionary of `np.ndarray` or `lists` (GH14293)

Deprecations

- `Series.reshape` and `Categorical.reshape` have been deprecated and will be removed in a subsequent release (GH12882, GH12882)
- `PeriodIndex.to_datetime` has been deprecated in favor of `PeriodIndex.to_timestamp` (GH8254)
- `Timestamp.to_datetime` has been deprecated in favor of `Timestamp.to_pydatetime` (GH8254)
- `Index.to_datetime` and `DatetimeIndex.to_datetime` have been deprecated in favor of `pd.to_datetime` (GH8254)
- `pandas.core.datetools` module has been deprecated and will be removed in a subsequent release (GH14094)
- `SparseList` has been deprecated and will be removed in a future version (GH13784)
- `DataFrame.to_html()` and `DataFrame.to_latex()` have dropped the `colSpace` parameter in favor of `col_space` (GH13857)
- `DataFrame.to_sql()` has deprecated the `flavor` parameter, as it is superfluous when SQLAlchemy is not installed (GH13611)
- Deprecated `read_csv` keywords:
  - `compact_ints` and `use_unsigned` have been deprecated and will be removed in a future version (GH13320)
  - `buffer_lines` has been deprecated and will be removed in a future version (GH13360)
  - `as_recarray` has been deprecated and will be removed in a future version (GH13373)
  - `skip_footer` has been deprecated in favor of `skipfooter` and will be removed in a future version (GH13349)
- top-level `pd.ordered_merge()` has been renamed to `pd.merge_ordered()` and the original name will be removed in a future version (GH13358)
- `Timestamp.offset` property (and named arg in the constructor), has been deprecated in favor of `freq` (GH12160)
- `pd.tseries.util.pivot_annual` is deprecated. Use `pivot_table` as alternative, an example is *here* (GH736)
- `pd.tseries.util.isleapyear` has been deprecated and will be removed in a subsequent release. Datetime-likes now have a `.is_leap_year` property (GH13727)

- `Panel4D` and `PanelND` constructors are deprecated and will be removed in a future version. The recommended way to represent these types of n-dimensional data are with the xarray package. pandas provides a `to_xarray()` method to automate this conversion (GH13564).
- `pandas.tseries.frequencies.get_standard_freq` is deprecated. Use `pandas.tseries.frequencies.to_offset(freq).rule_code` instead (GH13874)
- `pandas.tseries.frequencies.to_offset`'s `freqstr` keyword is deprecated in favor of `freq` (GH13874)
- `Categorical.from_array` has been deprecated and will be removed in a future version (GH13854)

Removal of prior version deprecations/changes

- The `SparsePanel` class has been removed (GH13778)
- The `pd.sandbox` module has been removed in favor of the external library `pandas-qt` (GH13670)
- The `pandas.io.data` and `pandas.io.wb` modules are removed in favor of the pandas-datareader package (GH13724).
- The `pandas.tools.rplot` module has been removed in favor of the seaborn package (GH13855)
- `DataFrame.to_csv()` has dropped the `engine` parameter, as was deprecated in 0.17.1 (GH11274, GH13419)
- `DataFrame.to_dict()` has dropped the `outtype` parameter in favor of `orient` (GH13627, GH8486)
- `pd.Categorical` has dropped setting of the `ordered` attribute directly in favor of the `set_ordered` method (GH13671)
- `pd.Categorical` has dropped the `levels` attribute in favor of `categories` (GH8376)
- `DataFrame.to_sql()` has dropped the `mysql` option for the `flavor` parameter (GH13611)
- `Panel.shift()` has dropped the `lags` parameter in favor of `periods` (GH14041)
- `pd.Index` has dropped the `diff` method in favor of `difference` (GH13669)
- `pd.DataFrame` has dropped the `to_wide` method in favor of `to_panel` (GH14039)
- `Series.to_csv` has dropped the `nanRep` parameter in favor of `na_rep` (GH13804)
- `Series.xs`, `DataFrame.xs`, `Panel.xs`, `Panel.major_xs`, and `Panel.minor_xs` have dropped the `copy` parameter (GH13781)
- `str.split` has dropped the `return_type` parameter in favor of `expand` (GH13701)
- Removal of the legacy time rules (offset aliases), deprecated since 0.17.0 (this has been alias since 0.8.0) (GH13590, GH13868). Now legacy time rules raises `ValueError`. For the list of currently supported offsets, see *here*.
- The default value for the `return_type` parameter for `DataFrame.plot.box` and `DataFrame.boxplot` changed from `None` to `"axes"`. These methods will now return a matplotlib axes by default instead of a dictionary of artists. See *here* (GH6581).
- The `tquery` and `uquery` functions in the `pandas.io.sql` module are removed (GH5950).

Performance improvements

- Improved performance of sparse `IntIndex.intersect` (GH13082)
- Improved performance of sparse arithmetic with `BlockIndex` when the number of blocks are large, though recommended to use `IntIndex` in such cases (GH13082)
- Improved performance of `DataFrame.quantile()` as it now operates per-block (GH11623)
- Improved performance of float64 hash table operations, fixing some very slow indexing and groupby operations in python 3 (GH13166, GH13334)
- Improved performance of `DataFrameGroupBy.transform` (GH12737)
- Improved performance of `Index` and `Series .duplicated` (GH10235)
- Improved performance of `Index.difference` (GH12044)
- Improved performance of `RangeIndex.is_monotonic_increasing` and `is_monotonic_decreasing` (GH13749)
- Improved performance of datetime string parsing in `DatetimeIndex` (GH13692)
- Improved performance of hashing `Period` (GH12817)
- Improved performance of `factorize` of datetime with timezone (GH13750)
- Improved performance of by lazily creating indexing hashtables on larger Indexes (GH14266)
- Improved performance of `groupby.groups` (GH14293)
- Unnecessary materializing of a MultiIndex when introspecting for memory usage (GH14308)

Bug fixes

- Bug in `groupby().shift()`, which could cause a segfault or corruption in rare circumstances when grouping by columns with missing values (GH13813)
- Bug in `groupby().cumsum()` calculating `cumprod` when `axis=1`. (GH13994)
- Bug in `pd.to_timedelta()` in which the `errors` parameter was not being respected (GH13613)
- Bug in `io.json.json_normalize()`, where non-ascii keys raised an exception (GH13213)
- Bug when passing a not-default-indexed `Series` as `xerr` or `yerr` in `.plot()` (GH11858)
- Bug in area plot draws legend incorrectly if subplot is enabled or legend is moved after plot (matplotlib 1.5.0 is required to draw area plot legend properly) (GH9161, GH13544)
- Bug in `DataFrame` assignment with an object-dtyped `Index` where the resultant column is mutable to the original object. (GH13522)
- Bug in matplotlib `AutoDataFormatter`; this restores the second scaled formatting and re-adds micro-second scaled formatting (GH13131)
- Bug in selection from a `HDFStore` with a fixed format and `start` and/or `stop` specified will now return the selected range (GH8287)
- Bug in `Categorical.from_codes()` where an unhelpful error was raised when an invalid `ordered` parameter was passed in (GH14058)
- Bug in `Series` construction from a tuple of integers on windows not returning default dtype (int64) (GH13646)
- Bug in `TimedeltaIndex` addition with a Datetime-like object where addition overflow was not being caught (GH14068)

- Bug in `.groupby(..).resample(..)` when the same object is called multiple times (GH13174)
- Bug in `.to_records()` when index name is a unicode string (GH13172)
- Bug in calling `.memory_usage()` on object which doesn't implement (GH12924)
- Regression in `Series.quantile` with nans (also shows up in `.median()` and `.describe()`); furthermore now names the `Series` with the quantile (GH13098, GH13146)
- Bug in `SeriesGroupBy.transform` with datetime values and missing groups (GH13191)
- Bug where empty `Series` were incorrectly coerced in datetime-like numeric operations (GH13844)
- Bug in `Categorical` constructor when passed a `Categorical` containing datetimes with timezones (GH14190)
- Bug in `Series.str.extractall()` with `str` index raises `ValueError` (GH13156)
- Bug in `Series.str.extractall()` with single group and quantifier (GH13382)
- Bug in `DatetimeIndex` and `Period` subtraction raises `ValueError` or `AttributeError` rather than `TypeError` (GH13078)
- Bug in `Index` and `Series` created with `NaN` and `NaT` mixed data may not have `datetime64` dtype (GH13324)
- Bug in `Index` and `Series` may ignore `np.datetime64('nat')` and `np.timdelta64('nat')` to infer dtype (GH13324)
- Bug in `PeriodIndex` and `Period` subtraction raises `AttributeError` (GH13071)
- Bug in `PeriodIndex` construction returning a `float64` index in some circumstances (GH13067)
- Bug in `.resample(..)` with a `PeriodIndex` not changing its `freq` appropriately when empty (GH13067)
- Bug in `.resample(..)` with a `PeriodIndex` not retaining its type or name with an empty `DataFrame` appropriately when empty (GH13212)
- Bug in `groupby(..).apply(..)` when the passed function returns scalar values per group (GH13468).
- Bug in `groupby(..).resample(..)` where passing some keywords would raise an exception (GH13235)
- Bug in `.tz_convert` on a tz-aware `DateTimeIndex` that relied on index being sorted for correct results (GH13306)
- Bug in `.tz_localize` with `dateutil.tz.tzlocal` may return incorrect result (GH13583)
- Bug in `DatetimeTZDtype` dtype with `dateutil.tz.tzlocal` cannot be regarded as valid dtype (GH13583)
- Bug in `pd.read_hdf()` where attempting to load an HDF file with a single dataset, that had one or more categorical columns, failed unless the key argument was set to the name of the dataset. (GH13231)
- Bug in `.rolling()` that allowed a negative integer window in construction of the `Rolling()` object, but would later fail on aggregation (GH13383)
- Bug in `Series` indexing with tuple-valued data and a numeric index (GH13509)
- Bug in printing `pd.DataFrame` where unusual elements with the `object` dtype were causing segfaults (GH13717)
- Bug in ranking `Series` which could result in segfaults (GH13445)
- Bug in various index types, which did not propagate the name of passed index (GH12309)
- Bug in `DatetimeIndex`, which did not honour the `copy=True` (GH13205)

- Bug in `DatetimeIndex.is_normalized` returns incorrectly for normalized date_range in case of local timezones (GH13459)
- Bug in `pd.concat` and `.append` may coerces `datetime64` and `timedelta` to `object` dtype containing python built-in `datetime` or `timedelta` rather than `Timestamp` or `Timedelta` (GH13626)
- Bug in `PeriodIndex.append` may raises `AttributeError` when the result is `object` dtype (GH13221)
- Bug in `CategoricalIndex.append` may accept normal `list` (GH13626)
- Bug in `pd.concat` and `.append` with the same timezone get reset to UTC (GH7795)
- Bug in `Series` and `DataFrame` `.append` raises `AmbiguousTimeError` if data contains datetime near DST boundary (GH13626)
- Bug in `DataFrame.to_csv()` in which float values were being quoted even though quotations were specified for non-numeric values only (GH12922, GH13259)
- Bug in `DataFrame.describe()` raising `ValueError` with only boolean columns (GH13898)
- Bug in `MultiIndex` slicing where extra elements were returned when level is non-unique (GH12896)
- Bug in `.str.replace` does not raise `TypeError` for invalid replacement (GH13438)
- Bug in `MultiIndex.from_arrays` which didn't check for input array lengths matching (GH13599)
- Bug in `cartesian_product` and `MultiIndex.from_product` which may raise with empty input arrays (GH12258)
- Bug in `pd.read_csv()` which may cause a segfault or corruption when iterating in large chunks over a stream/file under rare circumstances (GH13703)
- Bug in `pd.read_csv()` which caused errors to be raised when a dictionary containing scalars is passed in for `na_values` (GH12224)
- Bug in `pd.read_csv()` which caused BOM files to be incorrectly parsed by not ignoring the BOM (GH4793)
- Bug in `pd.read_csv()` with `engine='python'` which raised errors when a numpy array was passed in for `usecols` (GH12546)
- Bug in `pd.read_csv()` where the index columns were being incorrectly parsed when parsed as dates with a `thousands` parameter (GH14066)
- Bug in `pd.read_csv()` with `engine='python'` in which `NaN` values weren't being detected after data was converted to numeric values (GH13314)
- Bug in `pd.read_csv()` in which the `nrows` argument was not properly validated for both engines (GH10476)
- Bug in `pd.read_csv()` with `engine='python'` in which infinities of mixed-case forms were not being interpreted properly (GH13274)
- Bug in `pd.read_csv()` with `engine='python'` in which trailing `NaN` values were not being parsed (GH13320)
- Bug in `pd.read_csv()` with `engine='python'` when reading from a `tempfile.TemporaryFile` on Windows with Python 3 (GH13398)
- Bug in `pd.read_csv()` that prevents `usecols` kwarg from accepting single-byte unicode strings (GH13219)
- Bug in `pd.read_csv()` that prevents `usecols` from being an empty set (GH13402)
- Bug in `pd.read_csv()` in the C engine where the NULL character was not being parsed as NULL (GH14012)

- Bug in `pd.read_csv()` with `engine='c'` in which NULL `quotechar` was not accepted even though `quoting` was specified as `None` (GH13411)
- Bug in `pd.read_csv()` with `engine='c'` in which fields were not properly cast to float when quoting was specified as non-numeric (GH13411)
- Bug in `pd.read_csv()` in Python 2.x with non-UTF8 encoded, multi-character separated data (GH3404)
- Bug in `pd.read_csv()`, where aliases for utf-xx (e.g. UTF-xx, UTF_xx, utf_xx) raised UnicodeDecodeError (GH13549)
- Bug in `pd.read_csv`, `pd.read_table`, `pd.read_fwf`, `pd.read_stata` and `pd.read_sas` where files were opened by parsers but not closed if both `chunksize` and `iterator` were `None`. (GH13940)
- Bug in `StataReader`, `StataWriter`, `XportReader` and `SAS7BDATReader` where a file was not properly closed when an error was raised. (GH13940)
- Bug in `pd.pivot_table()` where `margins_name` is ignored when `aggfunc` is a list (GH13354)
- Bug in `pd.Series.str.zfill`, `center`, `ljust`, `rjust`, and `pad` when passing non-integers, did not raise `TypeError` (GH13598)
- Bug in checking for any null objects in a `TimedeltaIndex`, which always returned `True` (GH13603)
- Bug in `Series` arithmetic raises `TypeError` if it contains datetime-like as `object` dtype (GH13043)
- Bug `Series.isnull()` and `Series.notnull()` ignore `Period('NaT')` (GH13737)
- Bug `Series.fillna()` and `Series.dropna()` don't affect to `Period('NaT')` (GH13737
- Bug in `.fillna(value=np.nan)` incorrectly raises `KeyError` on a `category` dtyped `Series` (GH14021)
- Bug in extension dtype creation where the created types were not is/identical (GH13285)
- Bug in `.resample(..)` where incorrect warnings were triggered by IPython introspection (GH13618)
- Bug in `NaT - Period` raises `AttributeError` (GH13071)
- Bug in `Series` comparison may output incorrect result if rhs contains `NaT` (GH9005)
- Bug in `Series` and `Index` comparison may output incorrect result if it contains `NaT` with `object` dtype (GH13592)
- Bug in `Period` addition raises `TypeError` if `Period` is on right hand side (GH13069)
- Bug in `Period` and `Series` or `Index` comparison raises `TypeError` (GH13200)
- Bug in `pd.set_eng_float_format()` that would prevent NaN and Inf from formatting (GH11981)
- Bug in `.unstack` with `Categorical` dtype resets `.ordered` to `True` (GH13249)
- Clean some compile time warnings in datetime parsing (GH13607)
- Bug in `factorize` raises `AmbiguousTimeError` if data contains datetime near DST boundary (GH13750)
- Bug in `.set_index` raises `AmbiguousTimeError` if new index contains DST boundary and multi levels (GH12920)
- Bug in `.shift` raises `AmbiguousTimeError` if data contains datetime near DST boundary (GH13926)
- Bug in `pd.read_hdf()` returns incorrect result when a `DataFrame` with a `categorical` column and a query which doesn't match any values (GH13792)
- Bug in `.iloc` when indexing with a non lexsorted MultiIndex (GH13797)
- Bug in `.loc` when indexing with date strings in a reverse sorted `DatetimeIndex` (GH14316)

- Bug in `Series` comparison operators when dealing with zero dim NumPy arrays (GH13006)
- Bug in `.combine_first` may return incorrect `dtype` (GH7630, GH10567)
- Bug in `groupby` where `apply` returns different result depending on whether first result is `None` or not (GH12824)
- Bug in `groupby(..).nth()` where the group key is included inconsistently if called after `.head()/.tail()` (GH12839)
- Bug in `.to_html`, `.to_latex` and `.to_string` silently ignore custom datetime formatter passed through the `formatters` key word (GH10690)
- Bug in `DataFrame.iterrows()`, not yielding a `Series` subclasse if defined (GH13977)
- Bug in `pd.to_numeric` when `errors='coerce'` and input contains non-hashable objects (GH13324)
- Bug in invalid `Timedelta` arithmetic and comparison may raise `ValueError` rather than `TypeError` (GH13624)
- Bug in invalid datetime parsing in `to_datetime` and `DatetimeIndex` may raise `TypeError` rather than `ValueError` (GH11169, GH11287)
- Bug in `Index` created with tz-aware `Timestamp` and mismatched `tz` option incorrectly coerces timezone (GH13692)
- Bug in `DatetimeIndex` with nanosecond frequency does not include timestamp specified with `end` (GH13672)
- Bug in `` `Series `` when setting a slice with a `np.timedelta64` (GH14155)
- Bug in `Index` raises `OutOfBoundsDatetime` if `datetime` exceeds `datetime64[ns]` bounds, rather than coercing to `object` dtype (GH13663)
- Bug in `Index` may ignore specified `datetime64` or `timedelta64` passed as `dtype` (GH13981)
- Bug in `RangeIndex` can be created without no arguments rather than raises `TypeError` (GH13793)
- Bug in `.value_counts()` raises `OutOfBoundsDatetime` if data exceeds `datetime64[ns]` bounds (GH13663)
- Bug in `DatetimeIndex` may raise `OutOfBoundsDatetime` if input `np.datetime64` has other unit than `ns` (GH9114)
- Bug in `Series` creation with `np.datetime64` which has other unit than `ns` as `object` dtype results in incorrect values (GH13876)
- Bug in `resample` with timedelta data where data was casted to float (GH13119).
- Bug in `pd.isnull()` `pd.notnull()` raise `TypeError` if input datetime-like has other unit than `ns` (GH13389)
- Bug in `pd.merge()` may raise `TypeError` if input datetime-like has other unit than `ns` (GH13389)
- Bug in `HDFStore`/`read_hdf()` discarded `DatetimeIndex.name` if `tz` was set (GH13884)
- Bug in `Categorical.remove_unused_categories()` changes `.codes` dtype to platform int (GH13261)
- Bug in `groupby` with `as_index=False` returns all NaN's when grouping on multiple columns including a categorical one (GH13204)
- Bug in `df.groupby(...)[...]` where getitem with `Int64Index` raised an error (GH13731)

- Bug in the CSS classes assigned to `DataFrame.style` for index names. Previously they were assigned `"col_heading level<n> col<c>"` where `n` was the number of levels + 1. Now they are assigned `"index_name level<n>"`, where `n` is the correct level for that MultiIndex.
- Bug where `pd.read_gbq()` could throw `ImportError: No module named discovery` as a result of a naming conflict with another python package called apiclient (GH13454)
- Bug in `Index.union` returns an incorrect result with a named empty index (GH13432)
- Bugs in `Index.difference` and `DataFrame.join` raise in Python3 when using mixed-integer indexes (GH13432, GH12814)
- Bug in subtract tz-aware `datetime.datetime` from tz-aware `datetime64` series (GH14088)
- Bug in `.to_excel()` when DataFrame contains a MultiIndex which contains a label with a NaN value (GH13511)
- Bug in invalid frequency offset string like "D1", "-2-3H" may not raise `ValueError` (GH13930)
- Bug in `concat` and `groupby` for hierarchical frames with `RangeIndex` levels (GH13542).
- Bug in `Series.str.contains()` for Series containing only `NaN` values of `object` dtype (GH14171)
- Bug in `agg()` function on groupby dataframe changes dtype of `datetime64[ns]` column to `float64` (GH12821)
- Bug in using NumPy ufunc with `PeriodIndex` to add or subtract integer raise `IncompatibleFrequency`. Note that using standard operator like `+` or `-` is recommended, because standard operators use more efficient path (GH13980)
- Bug in operations on `NaT` returning `float` instead of `datetime64[ns]` (GH12941)
- Bug in `Series` flexible arithmetic methods (like `.add()`) raises `ValueError` when `axis=None` (GH13894)
- Bug in `DataFrame.to_csv()` with `MultiIndex` columns in which a stray empty line was added (GH6618)
- Bug in `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex.equals()` may return `True` when input isn't `Index` but contains the same values (GH13107)
- Bug in assignment against datetime with timezone may not work if it contains datetime near DST boundary (GH14146)
- Bug in `pd.eval()` and `HDFStore` query truncating long float literals with python 2 (GH14241)
- Bug in `Index` raises `KeyError` displaying incorrect column when column is not in the df and columns contains duplicate values (GH13822)
- Bug in `Period` and `PeriodIndex` creating wrong dates when frequency has combined offset aliases (GH13874)
- Bug in `.to_string()` when called with an integer `line_width` and `index=False` raises an UnboundLocalError exception because `idx` referenced before assignment.
- Bug in `eval()` where the `resolvers` argument would not accept a list (GH14095)
- Bugs in `stack`, `get_dummies`, `make_axis_dummies` which don't preserve categorical dtypes in (multi)indexes (GH13854)
- `PeriodIndex` can now accept `list` and `array` which contains `pd.NaT` (GH13430)
- Bug in `df.groupby` where `.median()` returns arbitrary values if grouped dataframe contains empty bins (GH13629)
- Bug in `Index.copy()` where `name` parameter was ignored (GH14302)

Contributors

A total of 117 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Alex Alekseyev
- Alex Vig +
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- Johnny Gill +
- Jordan Erenrich +
- Joris Van den Bossche
- Josh Howes +
- Jozef Brandys +
- Ka Wo Chen
- Kamil Sindi +
- Kerby Shedden
- Kernc +
- Kevin Sheppard
- Matthieu Brucher +
- Maximilian Roos
- Michael Scherer +
- Mike Graham +
- Mortada Mehyar
- Muhammad Haseeb Tariq +
- Nate George +
- Neil Parley +
- Nicolas Bonnotte
- OXPHOS
- Pan Deng / Zora +
- Paul +
- Paul Mestemaker +
- Pauli Virtanen
- Pawel Kordek +
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- Robert Kern +
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- Roy Keyes +
- Russell Smith +
- Sahil Dua +
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- Shawn Heide +
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- Stephen Kappel +
- Steve Choi +
- Stewart Henderson +
- Sudarshan Konge +
- Thomas A Caswell
- Tom Augspurger
- Tom Bird +
- Uwe Hoffmann +
- WillAyd +
- Xiang Zhang +
- YG-Riku +
- Yadunandan +
- Yaroslav Halchenko
- Yuichiro Kaneko +
- adneu
- agraboso +
- babakkeyvani +
- c123w +
- chris-b1
- cmazzullo +
- conquistador1492 +
- cr3 +
- dsm054
- gfyoung

- harshul1610 +
- iamsimha +
- jackieleng +
- mpuels +
- pijucha +
- priyankjain +
- sinhrks
- wcwagner +
- yui-knk +
- zhangjinjie +
- znmean +
- Yan Facai +

5.11 Version 0.18

5.11.1 Version 0.18.1 (May 3, 2016)

This is a minor bug-fix release from 0.18.0 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- `.groupby(...)` has been enhanced to provide convenient syntax when working with `.rolling(..)`, `.expanding(..)` and `.resample(..)` per group, see *here*
- `pd.to_datetime()` has gained the ability to assemble dates from a `DataFrame`, see *here*
- Method chaining improvements, see *here*.
- Custom business hour offset, see *here*.
- Many bug fixes in the handling of `sparse`, see *here*
- Expanded the *Tutorials section* with a feature on modern pandas, courtesy of @TomAugsburger. (GH13045).

What's new in v0.18.1

- *New features*
  - *Custom business hour*
  - *Method `.groupby(..)` syntax with window and resample operations*
  - *Method chaining improvements*
    - *Methods `.where()` and `.mask()`*
    - *Methods `.loc[]`, `.iloc[]`, `.ix[]`*
    - *Indexing with``[]``*
  - *Partial string indexing on `DatetimeIndex` when part of a `MultiIndex`*

- *Assembling datetimes*
- *Other enhancements*

- *Sparse changes*
- *API changes*
  - *Method `.groupby(..).nth()` changes*
  - *NumPy function compatibility*
  - *Using `.apply` on GroupBy resampling*
  - *Changes in `read_csv` exceptions*
  - *Method `to_datetime` error changes*
  - *Other API changes*
  - *Deprecations*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

New features

Custom business hour

The `CustomBusinessHour` is a mixture of `BusinessHour` and `CustomBusinessDay` which allows you to specify arbitrary holidays. For details, see *Custom Business Hour* (GH11514)

```
In [1]: from pandas.tseries.offsets import CustomBusinessHour

In [2]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [3]: bhour_us = CustomBusinessHour(calendar=USFederalHolidayCalendar())
```

Friday before MLK Day

```
In [4]: import datetime

In [5]: dt = datetime.datetime(2014, 1, 17, 15)

In [6]: dt + bhour_us
Out[6]: Timestamp('2014-01-17 16:00:00')
```

Tuesday after MLK Day (Monday is skipped because it's a holiday)

```
In [7]: dt + bhour_us * 2
Out[7]: Timestamp('2014-01-20 09:00:00')
```

Method `.groupby(..)` syntax with window and resample operations

`.groupby(...)` has been enhanced to provide convenient syntax when working with `.rolling(..)`, `.expanding(..)` and `.resample(..)` per group, see (GH12486, GH12738).

You can now use `.rolling(..)` and `.expanding(..)` as methods on groupbys. These return another deferred object (similar to what `.rolling()` and `.expanding()` do on ungrouped pandas objects). You can then operate on these `RollingGroupby` objects in a similar manner.

Previously you would have to do this to get a rolling window mean per-group:

```
In [8]: df = pd.DataFrame({"A": [1] * 20 + [2] * 12 + [3] * 8, "B": np.arange(40)})

In [9]: df
Out[9]:
    A   B
0   1   0
1   1   1
2   1   2
3   1   3
4   1   4
..  ..  ..
35  3  35
36  3  36
37  3  37
38  3  38
39  3  39

[40 rows x 2 columns]
```

```
In [10]: df.groupby("A").apply(lambda x: x.rolling(4).B.mean())
Out[10]:
A
1  0      NaN
   1      NaN
   2      NaN
   3      1.5
   4      2.5
         ...
3  35    33.5
   36    34.5
   37    35.5
   38    36.5
   39    37.5
Name: B, Length: 40, dtype: float64
```

Now you can do:

```
In [11]: df.groupby("A").rolling(4).B.mean()
Out[11]:
A
1  0      NaN
   1      NaN
   2      NaN
   3      1.5
   4      2.5
         ...
3  35    33.5
```

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```
   36    34.5
   37    35.5
   38    36.5
   39    37.5
Name: B, Length: 40, dtype: float64
```

For `.resample(..)` type of operations, previously you would have to:

```
In [12]: df = pd.DataFrame(
   ....:     {
   ....:         "date": pd.date_range(start="2016-01-01", periods=4, freq="W"),
   ....:         "group": [1, 1, 2, 2],
   ....:         "val": [5, 6, 7, 8],
   ....:     }
   ....: ).set_index("date")
   ....:

In [13]: df
Out[13]:
            group  val
date
2016-01-03      1    5
2016-01-10      1    6
2016-01-17      2    7
2016-01-24      2    8

[4 rows x 2 columns]
```

```
In [14]: df.groupby("group").apply(lambda x: x.resample("1D").ffill())
Out[14]:
                  group  val
group date
1     2016-01-03      1    5
      2016-01-04      1    5
      2016-01-05      1    5
      2016-01-06      1    5
      2016-01-07      1    5
...                 ...  ...
2     2016-01-20      2    7
      2016-01-21      2    7
      2016-01-22      2    7
      2016-01-23      2    7
      2016-01-24      2    8

[16 rows x 2 columns]
```

Now you can do:

```
In [15]: df.groupby("group").resample("1D").ffill()
Out[15]:
                  group  val
group date
1     2016-01-03      1    5
      2016-01-04      1    5
      2016-01-05      1    5
      2016-01-06      1    5
```

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```
      2016-01-07      1    5
...                  ...  ...
2     2016-01-20      2    7
      2016-01-21      2    7
      2016-01-22      2    7
      2016-01-23      2    7
      2016-01-24      2    8

[16 rows x 2 columns]
```

Method chaining improvements

The following methods / indexers now accept a `callable`. It is intended to make these more useful in method chains, see the *documentation*. (GH11485, GH12533)

- `.where()` and `.mask()`
- `.loc[]`, `iloc[]` and `.ix[]`
- `[]` indexing

Methods `.where()` and `.mask()`

These can accept a callable for the condition and `other` arguments.

```
In [16]: df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6], "C": [7, 8, 9]})

In [17]: df.where(lambda x: x > 4, lambda x: x + 10)
Out[17]:
    A   B  C
0  11  14  7
1  12   5  8
2  13   6  9

[3 rows x 3 columns]
```

Methods `.loc[]`, `.iloc[]`, `.ix[]`

These can accept a callable, and a tuple of callable as a slicer. The callable can return a valid boolean indexer or anything which is valid for these indexer's input.

```
# callable returns bool indexer
In [18]: df.loc[lambda x: x.A >= 2, lambda x: x.sum() > 10]
Out[18]:
   B  C
1  5  8
2  6  9

[2 rows x 2 columns]

# callable returns list of labels
In [19]: df.loc[lambda x: [1, 2], lambda x: ["A", "B"]]
```

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```
Out[19]:
   A  B
1  2  5
2  3  6

[2 rows x 2 columns]
```

Indexing with``[]``

Finally, you can use a callable in `[]` indexing of Series, DataFrame and Panel. The callable must return a valid input for `[]` indexing depending on its class and index type.

```
In [20]: df[lambda x: "A"]
Out[20]:
0    1
1    2
2    3
Name: A, Length: 3, dtype: int64
```

Using these methods / indexers, you can chain data selection operations without using temporary variable.

```
In [21]: bb = pd.read_csv("data/baseball.csv", index_col="id")

In [22]: (bb.groupby(["year", "team"]).sum().loc[lambda df: df.r > 100])
Out[22]:
           stint    g    ab    r    h  X2b  X3b  hr    rbi    sb   cs   bb     so  ␣
↪ibb   hbp    sh    sf  gidp
year team                                                                          ␣
↪
2007 CIN       6  379   745  101  203   35    2  36  125.0  10.0  1.0  105  127.0  14.
↪0   1.0   1.0  15.0  18.0
     DET       5  301  1062  162  283   54    4  37  144.0  24.0  7.0   97  176.0   3.
↪0  10.0   4.0   8.0  28.0
     HOU       4  311   926  109  218   47    6  14   77.0  10.0  4.0   60  212.0   3.
↪0   9.0  16.0   6.0  17.0
     LAN      11  413  1021  153  293   61    3  36  154.0   7.0  5.0  114  141.0   8.
↪0   9.0   3.0   8.0  29.0
     NYN      13  622  1854  240  509  101    3  61  243.0  22.0  4.0  174  310.0  24.
↪0  23.0  18.0  15.0  48.0
     SFN       5  482  1305  198  337   67    6  40  171.0  26.0  7.0  235  188.0  51.
↪0   8.0  16.0   6.0  41.0
     TEX       2  198   729  115  200   40    4  28  115.0  21.0  4.0   73  140.0   4.
↪0   5.0   2.0   8.0  16.0
     TOR       4  459  1408  187  378   96    2  58  223.0   4.0  2.0  190  265.0  16.
↪0  12.0   4.0  16.0  38.0

[8 rows x 18 columns]
```

Partial string indexing on `DatetimeIndex` when part of a `MultiIndex`

Partial string indexing now matches on `DateTimeIndex` when part of a `MultiIndex` (GH10331)

```
In [23]: dft2 = pd.DataFrame(
   ....:     np.random.randn(20, 1),
   ....:     columns=["A"],
   ....:     index=pd.MultiIndex.from_product(
   ....:         [pd.date_range("20130101", periods=10, freq="12H"), ["a", "b"]]
   ....:     ),
   ....: )
   ....:

In [24]: dft2
Out[24]:
                              A
2013-01-01 00:00:00 a  0.469112
                    b -0.282863
2013-01-01 12:00:00 a -1.509059
                    b -1.135632
2013-01-02 00:00:00 a  1.212112
...                         ...
2013-01-04 12:00:00 b  0.271860
2013-01-05 00:00:00 a -0.424972
                    b  0.567020
2013-01-05 12:00:00 a  0.276232
                    b -1.087401

[20 rows x 1 columns]

In [25]: dft2.loc["2013-01-05"]
Out[25]:
                              A
2013-01-05 00:00:00 a -0.424972
                    b  0.567020
2013-01-05 12:00:00 a  0.276232
                    b -1.087401

[4 rows x 1 columns]
```

On other levels

```
In [26]: idx = pd.IndexSlice

In [27]: dft2 = dft2.swaplevel(0, 1).sort_index()

In [28]: dft2
Out[28]:
                              A
a 2013-01-01 00:00:00  0.469112
  2013-01-01 12:00:00 -1.509059
  2013-01-02 00:00:00  1.212112
  2013-01-02 12:00:00  0.119209
  2013-01-03 00:00:00 -0.861849
...                         ...
b 2013-01-03 12:00:00  1.071804
  2013-01-04 00:00:00 -0.706771
```

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```
  2013-01-04 12:00:00  0.271860
  2013-01-05 00:00:00  0.567020
  2013-01-05 12:00:00 -1.087401

[20 rows x 1 columns]

In [29]: dft2.loc[idx[:, "2013-01-05"], :]
Out[29]:
                               A
a 2013-01-05 00:00:00 -0.424972
  2013-01-05 12:00:00  0.276232
b 2013-01-05 00:00:00  0.567020
  2013-01-05 12:00:00 -1.087401

[4 rows x 1 columns]
```

Assembling datetimes

`pd.to_datetime()` has gained the ability to assemble datetimes from a passed in `DataFrame` or a dict. (GH8158).

```
In [30]: df = pd.DataFrame(
   ....:     {"year": [2015, 2016], "month": [2, 3], "day": [4, 5], "hour": [2, 3]}
   ....: )
   ....:

In [31]: df
Out[31]:
   year  month  day  hour
0  2015      2    4     2
1  2016      3    5     3

[2 rows x 4 columns]
```

Assembling using the passed frame.

```
In [32]: pd.to_datetime(df)
Out[32]:
0   2015-02-04 02:00:00
1   2016-03-05 03:00:00
Length: 2, dtype: datetime64[ns]
```

You can pass only the columns that you need to assemble.

```
In [33]: pd.to_datetime(df[["year", "month", "day"]])
Out[33]:
0   2015-02-04
1   2016-03-05
Length: 2, dtype: datetime64[ns]
```

Other enhancements

- `pd.read_csv()` now supports `delim_whitespace=True` for the Python engine (GH12958)
- `pd.read_csv()` now supports opening ZIP files that contains a single CSV, via extension inference or explicit `compression='zip'` (GH12175)
- `pd.read_csv()` now supports opening files using xz compression, via extension inference or explicit `compression='xz'` is specified; `xz` compressions is also supported by `DataFrame.to_csv` in the same way (GH11852)
- `pd.read_msgpack()` now always gives writeable ndarrays even when compression is used (GH12359).
- `pd.read_msgpack()` now supports serializing and de-serializing categoricals with msgpack (GH12573)
- `.to_json()` now supports `NDFrames` that contain categorical and sparse data (GH10778)
- `interpolate()` now supports `method='akima'` (GH7588).
- `pd.read_excel()` now accepts path objects (e.g. `pathlib.Path`, `py.path.local`) for the file path, in line with other `read_*` functions (GH12655)
- Added `.weekday_name` property as a component to `DatetimeIndex` and the `.dt` accessor. (GH11128)
- `Index.take` now handles `allow_fill` and `fill_value` consistently (GH12631)

```
In [34]: idx = pd.Index([1.0, 2.0, 3.0, 4.0], dtype="float")

# default, allow_fill=True, fill_value=None
In [35]: idx.take([2, -1])
Out[35]: Float64Index([3.0, 4.0], dtype='float64')

In [36]: idx.take([2, -1], fill_value=True)
Out[36]: Float64Index([3.0, nan], dtype='float64')
```

- `Index` now supports `.str.get_dummies()` which returns `MultiIndex`, see *Creating Indicator Variables* (GH10008, GH10103)

```
In [37]: idx = pd.Index(["a|b", "a|c", "b|c"])

In [38]: idx.str.get_dummies("|")
Out[38]:
MultiIndex([(1, 1, 0),
            (1, 0, 1),
            (0, 1, 1)],
           names=['a', 'b', 'c'])
```

- `pd.crosstab()` has gained a `normalize` argument for normalizing frequency tables (GH12569). Examples in the updated docs *here*.
- `.resample(..).interpolate()` is now supported (GH12925)
- `.isin()` now accepts passed `sets` (GH12988)

Sparse changes

These changes conform sparse handling to return the correct types and work to make a smoother experience with indexing.

`SparseArray.take` now returns a scalar for scalar input, `SparseArray` for others. Furthermore, it handles a negative indexer with the same rule as `Index` (GH10560, GH12796)

```
s = pd.SparseArray([np.nan, np.nan, 1, 2, 3, np.nan, 4, 5, np.nan, 6])
s.take(0)
s.take([1, 2, 3])
```

- Bug in `SparseSeries[]` indexing with `Ellipsis` raises `KeyError` (GH9467)
- Bug in `SparseArray[]` indexing with tuples are not handled properly (GH12966)
- Bug in `SparseSeries.loc[]` with list-like input raises `TypeError` (GH10560)
- Bug in `SparseSeries.iloc[]` with scalar input may raise `IndexError` (GH10560)
- Bug in `SparseSeries.loc[]`, `.iloc[]` with `slice` returns `SparseArray`, rather than `SparseSeries` (GH10560)
- Bug in `SparseDataFrame.loc[]`, `.iloc[]` may results in dense `Series`, rather than `SparseSeries` (GH12787)
- Bug in `SparseArray` addition ignores `fill_value` of right hand side (GH12910)
- Bug in `SparseArray` mod raises `AttributeError` (GH12910)
- Bug in `SparseArray` pow calculates `1 ** np.nan` as `np.nan` which must be 1 (GH12910)
- Bug in `SparseArray` comparison output may incorrect result or raise `ValueError` (GH12971)
- Bug in `SparseSeries.__repr__` raises `TypeError` when it is longer than `max_rows` (GH10560)
- Bug in `SparseSeries.shape` ignores `fill_value` (GH10452)
- Bug in `SparseSeries` and `SparseArray` may have different `dtype` from its dense values (GH12908)
- Bug in `SparseSeries.reindex` incorrectly handle `fill_value` (GH12797)
- Bug in `SparseArray.to_frame()` results in `DataFrame`, rather than `SparseDataFrame` (GH9850)
- Bug in `SparseSeries.value_counts()` does not count `fill_value` (GH6749)
- Bug in `SparseArray.to_dense()` does not preserve `dtype` (GH10648)
- Bug in `SparseArray.to_dense()` incorrectly handle `fill_value` (GH12797)
- Bug in `pd.concat()` of `SparseSeries` results in dense (GH10536)
- Bug in `pd.concat()` of `SparseDataFrame` incorrectly handle `fill_value` (GH9765)
- Bug in `pd.concat()` of `SparseDataFrame` may raise `AttributeError` (GH12174)
- Bug in `SparseArray.shift()` may raise `NameError` or `TypeError` (GH12908)

API changes

Method `.groupby(..).nth()` changes

The index in `.groupby(..).nth()` output is now more consistent when the `as_index` argument is passed (GH11039):

```
In [39]: df = pd.DataFrame({"A": ["a", "b", "a"], "B": [1, 2, 3]})

In [40]: df
Out[40]:
   A  B
0  a  1
1  b  2
2  a  3

[3 rows x 2 columns]
```

Previous behavior:

```
In [3]: df.groupby('A', as_index=True)['B'].nth(0)
Out[3]:
0    1
1    2
Name: B, dtype: int64

In [4]: df.groupby('A', as_index=False)['B'].nth(0)
Out[4]:
0    1
1    2
Name: B, dtype: int64
```

New behavior:

```
In [41]: df.groupby("A", as_index=True)["B"].nth(0)
Out[41]:
A
a    1
b    2
Name: B, Length: 2, dtype: int64

In [42]: df.groupby("A", as_index=False)["B"].nth(0)
Out[42]:
0    1
1    2
Name: B, Length: 2, dtype: int64
```

Furthermore, previously, a `.groupby` would always sort, regardless if `sort=False` was passed with `.nth()`.

```
In [43]: np.random.seed(1234)

In [44]: df = pd.DataFrame(np.random.randn(100, 2), columns=["a", "b"])

In [45]: df["c"] = np.random.randint(0, 4, 100)
```

Previous behavior:

```
In [4]: df.groupby('c', sort=True).nth(1)
Out[4]:
          a         b
c
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524

In [5]: df.groupby('c', sort=False).nth(1)
Out[5]:
          a         b
c
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524
```

New behavior:

```
In [46]: df.groupby("c", sort=True).nth(1)
Out[46]:
          a         b
c
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524

[4 rows x 2 columns]

In [47]: df.groupby("c", sort=False).nth(1)
Out[47]:
          a         b
c
2 -0.720589  0.887163
3  0.859588 -0.636524
0 -0.334077  0.002118
1  0.036142 -2.074978

[4 rows x 2 columns]
```

NumPy function compatibility

Compatibility between pandas array-like methods (e.g. `sum` and `take`) and their `numpy` counterparts has been greatly increased by augmenting the signatures of the `pandas` methods so as to accept arguments that can be passed in from `numpy`, even if they are not necessarily used in the `pandas` implementation (GH12644, GH12638, GH12687)

- `.searchsorted()` for `Index` and `TimedeltaIndex` now accept a `sorter` argument to maintain compatibility with numpy's `searchsorted` function (GH12238)
- Bug in numpy compatibility of `np.round()` on a `Series` (GH12600)

An example of this signature augmentation is illustrated below:

```
sp = pd.SparseDataFrame([1, 2, 3])
sp
```

Previous behaviour:

```
In [2]: np.cumsum(sp, axis=0)
...
TypeError: cumsum() takes at most 2 arguments (4 given)
```

New behaviour:

```
np.cumsum(sp, axis=0)
```

Using `.apply` on GroupBy resampling

Using `apply` on resampling groupby operations (using a `pd.TimeGrouper`) now has the same output types as similar `apply` calls on other groupby operations. (GH11742).

```
In [48]: df = pd.DataFrame(
   ....:     {"date": pd.to_datetime(["10/10/2000", "11/10/2000"]), "value": [10, 13]}
   ....: )
   ....:

In [49]: df
Out[49]:
        date  value
0 2000-10-10     10
1 2000-11-10     13

[2 rows x 2 columns]
```

Previous behavior:

```
In [1]: df.groupby(pd.TimeGrouper(key='date',
   ...:                           freq='M')).apply(lambda x: x.value.sum())
Out[1]:
...
TypeError: cannot concatenate a non-NDFrame object

# Output is a Series
In [2]: df.groupby(pd.TimeGrouper(key='date',
   ...:                           freq='M')).apply(lambda x: x[['value']].sum())
Out[2]:
date
2000-10-31  value    10
2000-11-30  value    13
dtype: int64
```

New behavior:

```
# Output is a Series
In [55]: df.groupby(pd.TimeGrouper(key='date',
    ...:                           freq='M')).apply(lambda x: x.value.sum())
Out[55]:
date
2000-10-31    10
2000-11-30    13
Freq: M, dtype: int64
```

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```
# Output is a DataFrame
In [56]: df.groupby(pd.TimeGrouper(key='date',
    ...:                           freq='M')).apply(lambda x: x[['value']].sum())
Out[56]:
            value
date
2000-10-31     10
2000-11-30     13
```

Changes in `read_csv` exceptions

In order to standardize the `read_csv` API for both the `c` and `python` engines, both will now raise an `EmptyDataError`, a subclass of `ValueError`, in response to empty columns or header (GH12493, GH12506)

Previous behaviour:

```
In [1]: import io

In [2]: df = pd.read_csv(io.StringIO(''), engine='c')
...
ValueError: No columns to parse from file

In [3]: df = pd.read_csv(io.StringIO(''), engine='python')
...
StopIteration
```

New behaviour:

```
In [1]: df = pd.read_csv(io.StringIO(''), engine='c')
...
pandas.io.common.EmptyDataError: No columns to parse from file

In [2]: df = pd.read_csv(io.StringIO(''), engine='python')
...
pandas.io.common.EmptyDataError: No columns to parse from file
```

In addition to this error change, several others have been made as well:

- `CParserError` now sub-classes `ValueError` instead of just a `Exception` (GH12551)
- A `CParserError` is now raised instead of a generic `Exception` in `read_csv` when the `c` engine cannot parse a column (GH12506)
- A `ValueError` is now raised instead of a generic `Exception` in `read_csv` when the `c` engine encounters a `NaN` value in an integer column (GH12506)
- A `ValueError` is now raised instead of a generic `Exception` in `read_csv` when `true_values` is specified, and the `c` engine encounters an element in a column containing unencodable bytes (GH12506)
- `pandas.parser.OverflowError` exception has been removed and has been replaced with Python's built-in `OverflowError` exception (GH12506)
- `pd.read_csv()` no longer allows a combination of strings and integers for the `usecols` parameter (GH12678)

Method `to_datetime` error changes

Bugs in `pd.to_datetime()` when passing a `unit` with convertible entries and `errors='coerce'` or non-convertible with `errors='ignore'`. Furthermore, an `OutOfBoundsDateime` exception will be raised when an out-of-range value is encountered for that unit when `errors='raise'`. (GH11758, GH13052, GH13059)

Previous behaviour:

```
In [27]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[27]: NaT

In [28]: pd.to_datetime(11111111, unit='D', errors='ignore')
OverflowError: Python int too large to convert to C long

In [29]: pd.to_datetime(11111111, unit='D', errors='raise')
OverflowError: Python int too large to convert to C long
```

New behaviour:

```
In [2]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[2]: Timestamp('2014-12-31 16:31:00')

In [3]: pd.to_datetime(11111111, unit='D', errors='ignore')
Out[3]: 11111111

In [4]: pd.to_datetime(11111111, unit='D', errors='raise')
OutOfBoundsDatetime: cannot convert input with unit 'D'
```

Other API changes

- `.swaplevel()` for `Series`, `DataFrame`, `Panel`, and `MultiIndex` now features defaults for its first two parameters `i` and `j` that swap the two innermost levels of the index. (GH12934)
- `.searchsorted()` for `Index` and `TimedeltaIndex` now accept a `sorter` argument to maintain compatibility with numpy's `searchsorted` function (GH12238)
- `Period` and `PeriodIndex` now raises `IncompatibleFrequency` error which inherits `ValueError` rather than raw `ValueError` (GH12615)
- `Series.apply` for category dtype now applies the passed function to each of the `.categories` (and not the `.codes`), and returns a `category` dtype if possible (GH12473)
- `read_csv` will now raise a `TypeError` if `parse_dates` is neither a boolean, list, or dictionary (matches the doc-string) (GH5636)
- The default for `.query()/.eval()` is now `engine=None`, which will use `numexpr` if it's installed; otherwise it will fallback to the `python` engine. This mimics the pre-0.18.1 behavior if `numexpr` is installed (and which, previously, if numexpr was not installed, `.query()/.eval()` would raise). (GH12749)
- `pd.show_versions()` now includes `pandas_datareader` version (GH12740)
- Provide a proper `__name__` and `__qualname__` attributes for generic functions (GH12021)
- `pd.concat(ignore_index=True)` now uses `RangeIndex` as default (GH12695)
- `pd.merge()` and `DataFrame.join()` will show a `UserWarning` when merging/joining a single- with a multi-leveled dataframe (GH9455, GH12219)

- Compat with `scipy` > 0.17 for deprecated `piecewise_polynomial` interpolation method; support for the replacement `from_derivatives` method (GH12887)

Deprecations

- The method name `Index.sym_diff()` is deprecated and can be replaced by `Index.symmetric_difference()` (GH12591)
- The method name `Categorical.sort()` is deprecated in favor of `Categorical.sort_values()` (GH12882)

Performance improvements

- Improved speed of SAS reader (GH12656, GH12961)
- Performance improvements in `.groupby(..).cumcount()` (GH11039)
- Improved memory usage in `pd.read_csv()` when using `skiprows=an_integer` (GH13005)
- Improved performance of `DataFrame.to_sql` when checking case sensitivity for tables. Now only checks if table has been created correctly when table name is not lower case. (GH12876)
- Improved performance of `Period` construction and time series plotting (GH12903, GH11831).
- Improved performance of `.str.encode()` and `.str.decode()` methods (GH13008)
- Improved performance of `to_numeric` if input is numeric dtype (GH12777)
- Improved performance of sparse arithmetic with `IntIndex` (GH13036)

Bug fixes

- `usecols` parameter in `pd.read_csv` is now respected even when the lines of a CSV file are not even (GH12203)
- Bug in `groupby.transform(..)` when `axis=1` is specified with a non-monotonic ordered index (GH12713)
- Bug in `Period` and `PeriodIndex` creation raises `KeyError` if `freq="Minute"` is specified. Note that "Minute" freq is deprecated in v0.17.0, and recommended to use `freq="T"` instead (GH11854)
- Bug in `.resample(...).count()` with a `PeriodIndex` always raising a `TypeError` (GH12774)
- Bug in `.resample(...)` with a `PeriodIndex` casting to a `DatetimeIndex` when empty (GH12868)
- Bug in `.resample(...)` with a `PeriodIndex` when resampling to an existing frequency (GH12770)
- Bug in printing data which contains `Period` with different `freq` raises `ValueError` (GH12615)
- Bug in `Series` construction with `Categorical` and `dtype='category'` is specified (GH12574)
- Bugs in concatenation with a coercible dtype was too aggressive, resulting in different dtypes in output formatting when an object was longer than `display.max_rows` (GH12411, GH12045, GH11594, GH10571, GH12211)
- Bug in `float_format` option with option not being validated as a callable. (GH12706)
- Bug in `GroupBy.filter` when `dropna=False` and no groups fulfilled the criteria (GH12768)
- Bug in `__name__` of `.cum*` functions (GH12021)
- Bug in `.astype()` of a `Float64Inde/Int64Index` to an `Int64Index` (GH12881)

- Bug in round tripping an integer based index in `.to_json()/.read_json()` when `orient='index'` (the default) (GH12866)
- Bug in plotting `Categorical` dtypes cause error when attempting stacked bar plot (GH13019)
- Compat with >= `numpy` 1.11 for `NaT` comparisons (GH12969)
- Bug in `.drop()` with a non-unique `MultiIndex`. (GH12701)
- Bug in `.concat` of datetime tz-aware and naive DataFrames (GH12467)
- Bug in correctly raising a `ValueError` in `.resample(..).fillna(..)` when passing a non-string (GH12952)
- Bug fixes in various encoding and header processing issues in `pd.read_sas()` (GH12659, GH12654, GH12647, GH12809)
- Bug in `pd.crosstab()` where would silently ignore `aggfunc` if `values=None` (GH12569).
- Potential segfault in `DataFrame.to_json` when serialising `datetime.time` (GH11473).
- Potential segfault in `DataFrame.to_json` when attempting to serialise 0d array (GH11299).
- Segfault in `to_json` when attempting to serialise a `DataFrame` or `Series` with non-ndarray values; now supports serialization of `category`, `sparse`, and `datetime64[ns, tz]` dtypes (GH10778).
- Bug in `DataFrame.to_json` with unsupported dtype not passed to default handler (GH12554).
- Bug in `.align` not returning the sub-class (GH12983)
- Bug in aligning a `Series` with a `DataFrame` (GH13037)
- Bug in `ABCPanel` in which `Panel4D` was not being considered as a valid instance of this generic type (GH12810)
- Bug in consistency of `.name` on `.groupby(..).apply(..)` cases (GH12363)
- Bug in `Timestamp.__repr__` that caused `pprint` to fail in nested structures (GH12622)
- Bug in `Timedelta.min` and `Timedelta.max`, the properties now report the true minimum/maximum `timedeltas` as recognized by pandas. See the *documentation*. (GH12727)
- Bug in `.quantile()` with interpolation may coerce to `float` unexpectedly (GH12772)
- Bug in `.quantile()` with empty `Series` may return scalar rather than empty `Series` (GH12772)
- Bug in `.loc` with out-of-bounds in a large indexer would raise `IndexError` rather than `KeyError` (GH12527)
- Bug in resampling when using a `TimedeltaIndex` and `.asfreq()`, would previously not include the final fencepost (GH12926)
- Bug in equality testing with a `Categorical` in a `DataFrame` (GH12564)
- Bug in `GroupBy.first()`, `.last()` returns incorrect row when `TimeGrouper` is used (GH7453)
- Bug in `pd.read_csv()` with the `c` engine when specifying `skiprows` with newlines in quoted items (GH10911, GH12775)
- Bug in `DataFrame` timezone lost when assigning tz-aware datetime `Series` with alignment (GH12981)
- Bug in `.value_counts()` when `normalize=True` and `dropna=True` where nulls still contributed to the normalized count (GH12558)
- Bug in `Series.value_counts()` loses name if its dtype is `category` (GH12835)
- Bug in `Series.value_counts()` loses timezone info (GH12835)

- Bug in `Series.value_counts(normalize=True)` with `Categorical` raises `UnboundLocalError` (GH12835)
- Bug in `Panel.fillna()` ignoring `inplace=True` (GH12633)
- Bug in `pd.read_csv()` when specifying `names`, `usecols`, and `parse_dates` simultaneously with the `c` engine (GH9755)
- Bug in `pd.read_csv()` when specifying `delim_whitespace=True` and `lineterminator` simultaneously with the `c` engine (GH12912)
- Bug in `Series.rename`, `DataFrame.rename` and `DataFrame.rename_axis` not treating `Series` as mappings to relabel (GH12623).
- Clean in `.rolling.min` and `.rolling.max` to enhance dtype handling (GH12373)
- Bug in `groupby` where complex types are coerced to float (GH12902)
- Bug in `Series.map` raises `TypeError` if its dtype is `category` or tz-aware `datetime` (GH12473)
- Bugs on 32bit platforms for some test comparisons (GH12972)
- Bug in index coercion when falling back from `RangeIndex` construction (GH12893)
- Better error message in window functions when invalid argument (e.g. a float window) is passed (GH12669)
- Bug in slicing subclassed `DataFrame` defined to return subclassed `Series` may return normal `Series` (GH11559)
- Bug in `.str` accessor methods may raise `ValueError` if input has `name` and the result is `DataFrame` or `MultiIndex` (GH12617)
- Bug in `DataFrame.last_valid_index()` and `DataFrame.first_valid_index()` on empty frames (GH12800)
- Bug in `CategoricalIndex.get_loc` returns different result from regular `Index` (GH12531)
- Bug in `PeriodIndex.resample` where name not propagated (GH12769)
- Bug in `date_range` `closed` keyword and timezones (GH12684).
- Bug in `pd.concat` raises `AttributeError` when input data contains tz-aware datetime and timedelta (GH12620)
- Bug in `pd.concat` did not handle empty `Series` properly (GH11082)
- Bug in `.plot.bar` alignment when `width` is specified with `int` (GH12979)
- Bug in `fill_value` is ignored if the argument to a binary operator is a constant (GH12723)
- Bug in `pd.read_html()` when using bs4 flavor and parsing table with a header and only one column (GH9178)
- Bug in `.pivot_table` when `margins=True` and `dropna=True` where nulls still contributed to margin count (GH12577)
- Bug in `.pivot_table` when `dropna=False` where table index/column names disappear (GH12133)
- Bug in `pd.crosstab()` when `margins=True` and `dropna=False` which raised (GH12642)
- Bug in `Series.name` when `name` attribute can be a hashable type (GH12610)
- Bug in `.describe()` resets categorical columns information (GH11558)
- Bug where `loffset` argument was not applied when calling `resample().count()` on a timeseries (GH12725)
- `pd.read_excel()` now accepts column names associated with keyword argument `names` (GH12870)

- Bug in `pd.to_numeric()` with `Index` returns `np.ndarray`, rather than `Index` (GH12777)
- Bug in `pd.to_numeric()` with datetime-like may raise `TypeError` (GH12777)
- Bug in `pd.to_numeric()` with scalar raises `ValueError` (GH12777)

Contributors

A total of 60 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Andrew Fiore-Gartland +
- Bastiaan +
- Benoît Vinot +
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- jonaslb +
- kotrfa +
- nileracecrew +
- onesandzeroes
- rs2 +
- sinhrks
- tsdlovell +

5.11.2 Version 0.18.0 (March 13, 2016)

This is a major release from 0.17.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Warning: pandas >= 0.18.0 no longer supports compatibility with Python version 2.6 and 3.3 (GH7718, GH11273)

Warning: `numexpr` version 2.4.4 will now show a warning and not be used as a computation back-end for pandas because of some buggy behavior. This does not affect other versions (>= 2.1 and >= 2.4.6). (GH12489)

Highlights include:

- Moving and expanding window functions are now methods on Series and DataFrame, similar to `.groupby`, see *here*.
- Adding support for a `RangeIndex` as a specialized form of the `Int64Index` for memory savings, see *here*.
- API breaking change to the `.resample` method to make it more `.groupby` like, see *here*.
- Removal of support for positional indexing with floats, which was deprecated since 0.14.0. This will now raise a `TypeError`, see *here*.
- The `.to_xarray()` function has been added for compatibility with the xarray package, see *here*.
- The `read_sas` function has been enhanced to read `sas7bdat` files, see *here*.
- Addition of the *.str.extractall() method*, and API changes to the *.str.extract() method* and *.str.cat() method*.
- `pd.test()` top-level nose test runner is available (GH4327).

Check the *API Changes* and *deprecations* before updating.

What's new in v0.18.0

- *New features*
  - *Window functions are now methods*
  - *Changes to rename*
  - *Range Index*
  - *Changes to str.extract*
  - *Addition of str.extractall*
  - *Changes to str.cat*
  - *Datetimelike rounding*
  - *Formatting of integers in FloatIndex*
  - *Changes to dtype assignment behaviors*
  - *Method to_xarray*
  - *Latex representation*

        - *pd.read_sas() changes*
        - *Other enhancements*
    - *Backwards incompatible API changes*
        - *NaT and Timedelta operations*
        - *Changes to msgpack*
        - *Signature change for .rank*
        - *Bug in QuarterBegin with n=0*
        - *Resample API*
            * *Downsampling*
            * *Upsampling*
            * *Previous API will work but with deprecations*
        - *Changes to eval*
        - *Other API changes*
        - *Deprecations*
        - *Removal of deprecated float indexers*
        - *Removal of prior version deprecations/changes*
    - *Performance improvements*
    - *Bug fixes*
    - *Contributors*

New features

Window functions are now methods

Window functions have been refactored to be methods on `Series/DataFrame` objects, rather than top-level functions, which are now deprecated. This allows these window-type functions, to have a similar API to that of `.groupby`. See the full documentation *here* (GH11603, GH12373)

```
In [1]: np.random.seed(1234)

In [2]: df = pd.DataFrame({'A': range(10), 'B': np.random.randn(10)})

In [3]: df
Out[3]:
   A         B
0  0  0.471435
1  1 -1.190976
2  2  1.432707
3  3 -0.312652
4  4 -0.720589
5  5  0.887163
6  6  0.859588
7  7 -0.636524
8  8  0.015696
```

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```
9  9 -2.242685

[10 rows x 2 columns]
```

Previous behavior:

```
In [8]: pd.rolling_mean(df, window=3)
        FutureWarning: pd.rolling_mean is deprecated for DataFrame and will be␣
↪removed in a future version, replace with
                    DataFrame.rolling(window=3,center=False).mean()
Out[8]:
    A         B
0 NaN       NaN
1 NaN       NaN
2   1  0.237722
3   2 -0.023640
4   3  0.133155
5   4 -0.048693
6   5  0.342054
7   6  0.370076
8   7  0.079587
9   8 -0.954504
```

New behavior:

```
In [4]: r = df.rolling(window=3)
```

These show a descriptive repr

```
In [5]: r
Out[5]: Rolling [window=3,center=False,axis=0]
```

with tab-completion of available methods and properties.

```
In [9]: r.<TAB>  # noqa E225, E999
r.A           r.agg         r.apply       r.count       r.exclusions  r.max         r.
↪median       r.name        r.skew        r.sum
r.B           r.aggregate   r.corr        r.cov         r.kurt        r.mean        r.
↪min          r.quantile    r.std         r.var
```

The methods operate on the `Rolling` object itself

```
In [6]: r.mean()
Out[6]:
     A         B
0  NaN       NaN
1  NaN       NaN
2  1.0  0.237722
3  2.0 -0.023640
4  3.0  0.133155
5  4.0 -0.048693
6  5.0  0.342054
7  6.0  0.370076
8  7.0  0.079587
9  8.0 -0.954504

[10 rows x 2 columns]
```

They provide getitem accessors

```
In [7]: r['A'].mean()
Out[7]:
0    NaN
1    NaN
2    1.0
3    2.0
4    3.0
5    4.0
6    5.0
7    6.0
8    7.0
9    8.0
Name: A, Length: 10, dtype: float64
```

And multiple aggregations

```
In [8]: r.agg({'A': ['mean', 'std'],
   ...:        'B': ['mean', 'std']})
   ...:
Out[8]:
     A              B
  mean  std      mean       std
0  NaN  NaN       NaN       NaN
1  NaN  NaN       NaN       NaN
2  1.0  1.0  0.237722  1.327364
3  2.0  1.0 -0.023640  1.335505
4  3.0  1.0  0.133155  1.143778
5  4.0  1.0 -0.048693  0.835747
6  5.0  1.0  0.342054  0.920379
7  6.0  1.0  0.370076  0.871850
8  7.0  1.0  0.079587  0.750099
9  8.0  1.0 -0.954504  1.162285

[10 rows x 4 columns]
```

Changes to rename

`Series.rename` and `NDFrame.rename_axis` can now take a scalar or list-like argument for altering the Series or axis *name*, in addition to their old behaviors of altering labels. (GH9494, GH11965)

```
In [9]: s = pd.Series(np.random.randn(5))

In [10]: s.rename('newname')
Out[10]:
0    1.150036
1    0.991946
2    0.953324
3   -2.021255
4   -0.334077
Name: newname, Length: 5, dtype: float64
```

```
In [11]: df = pd.DataFrame(np.random.randn(5, 2))

In [12]: (df.rename_axis("indexname")
```

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```
   ....:     .rename_axis("columns_name", axis="columns"))
   ....:
Out[12]:
columns_name         0         1
indexname
0              0.002118  0.405453
1              0.289092  1.321158
2             -1.546906 -0.202646
3             -0.655969  0.193421
4              0.553439  1.318152

[5 rows x 2 columns]
```

The new functionality works well in method chains. Previously these methods only accepted functions or dicts mapping a *label* to a new label. This continues to work as before for function or dict-like values.

Range Index

A `RangeIndex` has been added to the `Int64Index` sub-classes to support a memory saving alternative for common use cases. This has a similar implementation to the python `range` object (`xrange` in python 2), in that it only stores the start, stop, and step values for the index. It will transparently interact with the user API, converting to `Int64Index` if needed.

This will now be the default constructed index for `NDFrame` objects, rather than previous an `Int64Index`. (GH939, GH12070, GH12071, GH12109, GH12888)

Previous behavior:

```
In [3]: s = pd.Series(range(1000))

In [4]: s.index
Out[4]:
Int64Index([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,
            ...
            990, 991, 992, 993, 994, 995, 996, 997, 998, 999], dtype='int64',␣
↪length=1000)

In [6]: s.index.nbytes
Out[6]: 8000
```

New behavior:

```
In [13]: s = pd.Series(range(1000))

In [14]: s.index
Out[14]: RangeIndex(start=0, stop=1000, step=1)

In [15]: s.index.nbytes
Out[15]: 128
```

Changes to str.extract

The *.str.extract* method takes a regular expression with capture groups, finds the first match in each subject string, and returns the contents of the capture groups (GH11386).

In v0.18.0, the `expand` argument was added to `extract`.

- `expand=False`: it returns a `Series`, `Index`, or `DataFrame`, depending on the subject and regular expression pattern (same behavior as pre-0.18.0).
- `expand=True`: it always returns a `DataFrame`, which is more consistent and less confusing from the perspective of a user.

Currently the default is `expand=None` which gives a `FutureWarning` and uses `expand=False`. To avoid this warning, please explicitly specify `expand`.

```
In [1]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'[ab](\d)', expand=None)
FutureWarning: currently extract(expand=None) means expand=False (return Index/Series/
↪DataFrame)
but in a future version of pandas this will be changed to expand=True (return␣
↪DataFrame)

Out[1]:
0      1
1      2
2    NaN
dtype: object
```

Extracting a regular expression with one group returns a Series if `expand=False`.

```
In [16]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'[ab](\d)', expand=False)
Out[16]:
0      1
1      2
2    NaN
Length: 3, dtype: object
```

It returns a `DataFrame` with one column if `expand=True`.

```
In [17]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'[ab](\d)', expand=True)
Out[17]:
     0
0    1
1    2
2  NaN

[3 rows x 1 columns]
```

Calling on an `Index` with a regex with exactly one capture group returns an `Index` if `expand=False`.

```
In [18]: s = pd.Series(["a1", "b2", "c3"], ["A11", "B22", "C33"])

In [19]: s.index
Out[19]: Index(['A11', 'B22', 'C33'], dtype='object')

In [20]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=False)
Out[20]: Index(['A', 'B', 'C'], dtype='object', name='letter')
```

It returns a `DataFrame` with one column if `expand=True`.

```
In [21]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=True)
Out[21]:
  letter
0      A
1      B
2      C

[3 rows x 1 columns]
```

Calling on an `Index` with a regex with more than one capture group raises `ValueError` if `expand=False`.

```
>>> s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=False)
ValueError: only one regex group is supported with Index
```

It returns a `DataFrame` if `expand=True`.

```
In [22]: s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=True)
Out[22]:
  letter   1
0      A  11
1      B  22
2      C  33

[3 rows x 2 columns]
```

In summary, `extract(expand=True)` always returns a `DataFrame` with a row for every subject string, and a column for every capture group.

Addition of str.extractall

The *.str.extractall* method was added (GH11386). Unlike `extract`, which returns only the first match.

```
In [23]: s = pd.Series(["a1a2", "b1", "c1"], ["A", "B", "C"])

In [24]: s
Out[24]:
A    a1a2
B      b1
C      c1
Length: 3, dtype: object

In [25]: s.str.extract(r"(?P<letter>[ab])(?P<digit>\d)", expand=False)
Out[25]:
  letter digit
A      a     1
B      b     1
C    NaN   NaN

[3 rows x 2 columns]
```

The `extractall` method returns all matches.

```
In [26]: s.str.extractall(r"(?P<letter>[ab])(?P<digit>\d)")
Out[26]:
        letter digit
  match
```

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```
A 0          a     1
  1          a     2
B 0          b     1

[3 rows x 2 columns]
```

Changes to str.cat

The method `.str.cat()` concatenates the members of a `Series`. Before, if `NaN` values were present in the Series, calling `.str.cat()` on it would return `NaN`, unlike the rest of the `Series.str.*` API. This behavior has been amended to ignore `NaN` values by default. (GH11435).

A new, friendlier `ValueError` is added to protect against the mistake of supplying the `sep` as an arg, rather than as a kwarg. (GH11334).

```
In [27]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(sep=' ')
Out[27]: 'a b c'

In [28]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(sep=' ', na_rep='?')
Out[28]: 'a b ? c'
```

```
In [2]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(' ')
ValueError: Did you mean to supply a ``sep`` keyword?
```

Datetimelike rounding

`DatetimeIndex`, `Timestamp`, `TimedeltaIndex`, `Timedelta` have gained the `.round()`, `.floor()` and `.ceil()` method for datetimelike rounding, flooring and ceiling. (GH4314, GH11963)

Naive datetimes

```
In [29]: dr = pd.date_range('20130101 09:12:56.1234', periods=3)

In [30]: dr
Out[30]:
DatetimeIndex(['2013-01-01 09:12:56.123400', '2013-01-02 09:12:56.123400',
               '2013-01-03 09:12:56.123400'],
              dtype='datetime64[ns]', freq='D')

In [31]: dr.round('s')
Out[31]:
DatetimeIndex(['2013-01-01 09:12:56', '2013-01-02 09:12:56',
               '2013-01-03 09:12:56'],
              dtype='datetime64[ns]', freq=None)

# Timestamp scalar
In [32]: dr[0]
Out[32]: Timestamp('2013-01-01 09:12:56.123400', freq='D')

In [33]: dr[0].round('10s')
Out[33]: Timestamp('2013-01-01 09:13:00')
```

Tz-aware are rounded, floored and ceiled in local times

```
In [34]: dr = dr.tz_localize('US/Eastern')

In [35]: dr
Out[35]:
DatetimeIndex(['2013-01-01 09:12:56.123400-05:00',
               '2013-01-02 09:12:56.123400-05:00',
               '2013-01-03 09:12:56.123400-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)

In [36]: dr.round('s')
Out[36]:
DatetimeIndex(['2013-01-01 09:12:56-05:00', '2013-01-02 09:12:56-05:00',
               '2013-01-03 09:12:56-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

Timedeltas

```
In [37]: t = pd.timedelta_range('1 days 2 hr 13 min 45 us', periods=3, freq='d')

In [38]: t
Out[38]:
TimedeltaIndex(['1 days 02:13:00.000045', '2 days 02:13:00.000045',
                '3 days 02:13:00.000045'],
               dtype='timedelta64[ns]', freq='D')

In [39]: t.round('10min')
Out[39]: TimedeltaIndex(['1 days 02:10:00', '2 days 02:10:00', '3 days 02:10:00'],␣
↪dtype='timedelta64[ns]', freq=None)

# Timedelta scalar
In [40]: t[0]
Out[40]: Timedelta('1 days 02:13:00.000045')

In [41]: t[0].round('2h')
Out[41]: Timedelta('1 days 02:00:00')
```

In addition, `.round()`, `.floor()` and `.ceil()` will be available through the `.dt` accessor of `Series`.

```
In [42]: s = pd.Series(dr)

In [43]: s
Out[43]:
0   2013-01-01 09:12:56.123400-05:00
1   2013-01-02 09:12:56.123400-05:00
2   2013-01-03 09:12:56.123400-05:00
Length: 3, dtype: datetime64[ns, US/Eastern]

In [44]: s.dt.round('D')
Out[44]:
0   2013-01-01 00:00:00-05:00
1   2013-01-02 00:00:00-05:00
2   2013-01-03 00:00:00-05:00
Length: 3, dtype: datetime64[ns, US/Eastern]
```

Formatting of integers in FloatIndex

Integers in `FloatIndex`, e.g. 1., are now formatted with a decimal point and a `0` digit, e.g. `1.0` (GH11713) This change not only affects the display to the console, but also the output of IO methods like `.to_csv` or `.to_html`.

Previous behavior:

```
In [2]: s = pd.Series([1, 2, 3], index=np.arange(3.))

In [3]: s
Out[3]:
0    1
1    2
2    3
dtype: int64

In [4]: s.index
Out[4]: Float64Index([0.0, 1.0, 2.0], dtype='float64')

In [5]: print(s.to_csv(path=None))
0,1
1,2
2,3
```

New behavior:

```
In [45]: s = pd.Series([1, 2, 3], index=np.arange(3.))

In [46]: s
Out[46]:
0.0    1
1.0    2
2.0    3
Length: 3, dtype: int64

In [47]: s.index
Out[47]: Float64Index([0.0, 1.0, 2.0], dtype='float64')

In [48]: print(s.to_csv(path_or_buf=None, header=False))
0.0,1
1.0,2
2.0,3
```

Changes to dtype assignment behaviors

When a DataFrame's slice is updated with a new slice of the same dtype, the dtype of the DataFrame will now remain the same. (GH10503)

Previous behavior:

```
In [5]: df = pd.DataFrame({'a': [0, 1, 1],
                           'b': pd.Series([100, 200, 300], dtype='uint32')})

In [7]: df.dtypes
Out[7]:
a     int64
```

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```
b    uint32
dtype: object

In [8]: ix = df['a'] == 1

In [9]: df.loc[ix, 'b'] = df.loc[ix, 'b']

In [11]: df.dtypes
Out[11]:
a    int64
b    int64
dtype: object
```

New behavior:

```
In [49]: df = pd.DataFrame({'a': [0, 1, 1],
   ....:                    'b': pd.Series([100, 200, 300], dtype='uint32')})
   ....:

In [50]: df.dtypes
Out[50]:
a     int64
b    uint32
Length: 2, dtype: object

In [51]: ix = df['a'] == 1

In [52]: df.loc[ix, 'b'] = df.loc[ix, 'b']

In [53]: df.dtypes
Out[53]:
a     int64
b    uint32
Length: 2, dtype: object
```

When a DataFrame's integer slice is partially updated with a new slice of floats that could potentially be down-casted to integer without losing precision, the dtype of the slice will be set to float instead of integer.

Previous behavior:

```
In [4]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
                          columns=list('abc'),
                          index=[[4,4,8], [8,10,12]])

In [5]: df
Out[5]:
      a  b  c
4 8   1  2  3
  10  4  5  6
8 12  7  8  9

In [7]: df.ix[4, 'c'] = np.array([0., 1.])

In [8]: df
Out[8]:
      a  b  c
4 8   1  2  0
```

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```
  10  4  5  1
8 12  7  8  9
```

New behavior:

```
In [54]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
   ....:                   columns=list('abc'),
   ....:                   index=[[4,4,8], [8,10,12]])
   ....:

In [55]: df
Out[55]:
      a  b  c
4 8   1  2  3
  10  4  5  6
8 12  7  8  9

[3 rows x 3 columns]

In [56]: df.loc[4, 'c'] = np.array([0., 1.])

In [57]: df
Out[57]:
      a  b    c
4 8   1  2  0.0
  10  4  5  1.0
8 12  7  8  9.0

[3 rows x 3 columns]
```

Method to_xarray

In a future version of pandas, we will be deprecating `Panel` and other > 2 ndim objects. In order to provide for continuity, all `NDFrame` objects have gained the `.to_xarray()` method in order to convert to `xarray` objects, which has a pandas-like interface for > 2 ndim. (GH11972)

See the xarray full-documentation here.

```
In [1]: p = Panel(np.arange(2*3*4).reshape(2,3,4))

In [2]: p.to_xarray()
Out[2]:
<xarray.DataArray (items: 2, major_axis: 3, minor_axis: 4)>
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]],

       [[12, 13, 14, 15],
        [16, 17, 18, 19],
        [20, 21, 22, 23]]])
Coordinates:
  * items       (items) int64 0 1
  * major_axis  (major_axis) int64 0 1 2
  * minor_axis  (minor_axis) int64 0 1 2 3
```

Latex representation

`DataFrame` has gained a `._repr_latex_()` method in order to allow for conversion to latex in a ipython/jupyter notebook using nbconvert. (GH11778)

Note that this must be activated by setting the option `pd.display.latex.repr=True` (GH12182)

For example, if you have a jupyter notebook you plan to convert to latex using nbconvert, place the statement `pd.display.latex.repr=True` in the first cell to have the contained DataFrame output also stored as latex.

The options `display.latex.escape` and `display.latex.longtable` have also been added to the configuration and are used automatically by the `to_latex` method. See the *available options docs* for more info.

`pd.read_sas()` changes

`read_sas` has gained the ability to read SAS7BDAT files, including compressed files. The files can be read in entirety, or incrementally. For full details see *here*. (GH4052)

Other enhancements

- Handle truncated floats in SAS xport files (GH11713)
- Added option to hide index in `Series.to_string` (GH11729)
- `read_excel` now supports s3 urls of the format `s3://bucketname/filename` (GH11447)
- add support for `AWS_S3_HOST` env variable when reading from s3 (GH12198)
- A simple version of `Panel.round()` is now implemented (GH11763)
- For Python 3.x, `round(DataFrame)`, `round(Series)`, `round(Panel)` will work (GH11763)
- `sys.getsizeof(obj)` returns the memory usage of a pandas object, including the values it contains (GH11597)
- `Series` gained an `is_unique` attribute (GH11946)
- `DataFrame.quantile` and `Series.quantile` now accept `interpolation` keyword (GH10174).
- Added `DataFrame.style.format` for more flexible formatting of cell values (GH11692)
- `DataFrame.select_dtypes` now allows the `np.float16` type code (GH11990)
- `pivot_table()` now accepts most iterables for the `values` parameter (GH12017)
- Added Google `BigQuery` service account authentication support, which enables authentication on remote servers. (GH11881, GH12572). For further details see here
- `HDFStore` is now iterable: `for k in store` is equivalent to `for k in store.keys()` (GH12221).
- Add missing methods/fields to `.dt` for `Period` (GH8848)
- The entire code base has been `PEP`-ified (GH12096)

Backwards incompatible API changes

- the leading white spaces have been removed from the output of `.to_string(index=False)` method (GH11833)
- the `out` parameter has been removed from the `Series.round()` method. (GH11763)
- `DataFrame.round()` leaves non-numeric columns unchanged in its return, rather than raises. (GH11885)
- `DataFrame.head(0)` and `DataFrame.tail(0)` return empty frames, rather than `self`. (GH11937)
- `Series.head(0)` and `Series.tail(0)` return empty series, rather than `self`. (GH11937)
- `to_msgpack` and `read_msgpack` encoding now defaults to `'utf-8'`. (GH12170)
- the order of keyword arguments to text file parsing functions (`.read_csv()`, `.read_table()`, `.read_fwf()`) changed to group related arguments. (GH11555)
- `NaTType.isoformat` now returns the string `'NaT` to allow the result to be passed to the constructor of `Timestamp`. (GH12300)

NaT and Timedelta operations

`NaT` and `Timedelta` have expanded arithmetic operations, which are extended to `Series` arithmetic where applicable. Operations defined for `datetime64[ns]` or `timedelta64[ns]` are now also defined for `NaT` (GH11564).

`NaT` now supports arithmetic operations with integers and floats.

```
In [58]: pd.NaT * 1
Out[58]: NaT

In [59]: pd.NaT * 1.5
Out[59]: NaT

In [60]: pd.NaT / 2
Out[60]: NaT

In [61]: pd.NaT * np.nan
Out[61]: NaT
```

`NaT` defines more arithmetic operations with `datetime64[ns]` and `timedelta64[ns]`.

```
In [62]: pd.NaT / pd.NaT
Out[62]: nan

In [63]: pd.Timedelta('1s') / pd.NaT
Out[63]: nan
```

`NaT` may represent either a `datetime64[ns]` null or a `timedelta64[ns]` null. Given the ambiguity, it is treated as a `timedelta64[ns]`, which allows more operations to succeed.

```
In [64]: pd.NaT + pd.NaT
Out[64]: NaT

# same as
In [65]: pd.Timedelta('1s') + pd.Timedelta('1s')
Out[65]: Timedelta('0 days 00:00:02')
```

as opposed to

```
In [3]: pd.Timestamp('19900315') + pd.Timestamp('19900315')
TypeError: unsupported operand type(s) for +: 'Timestamp' and 'Timestamp'
```

However, when wrapped in a `Series` whose `dtype` is `datetime64[ns]` or `timedelta64[ns]`, the `dtype` information is respected.

```
In [1]: pd.Series([pd.NaT], dtype='<M8[ns]') + pd.Series([pd.NaT], dtype='<M8[ns]')
TypeError: can only operate on a datetimes for subtraction,
           but the operator [__add__] was passed
```

```
In [66]: pd.Series([pd.NaT], dtype='<m8[ns]') + pd.Series([pd.NaT], dtype='<m8[ns]')
Out[66]:
0   NaT
Length: 1, dtype: timedelta64[ns]
```

`Timedelta` division by `floats` now works.

```
In [67]: pd.Timedelta('1s') / 2.0
Out[67]: Timedelta('0 days 00:00:00.500000')
```

Subtraction by `Timedelta` in a `Series` by a `Timestamp` works (GH11925)

```
In [68]: ser = pd.Series(pd.timedelta_range('1 day', periods=3))

In [69]: ser
Out[69]:
0   1 days
1   2 days
2   3 days
Length: 3, dtype: timedelta64[ns]

In [70]: pd.Timestamp('2012-01-01') - ser
Out[70]:
0   2011-12-31
1   2011-12-30
2   2011-12-29
Length: 3, dtype: datetime64[ns]
```

`NaT.isoformat()` now returns `'NaT'`. This change allows `pd.Timestamp` to rehydrate any timestamp like object from its isoformat (GH12300).

Changes to msgpack

Forward incompatible changes in `msgpack` writing format were made over 0.17.0 and 0.18.0; older versions of pandas cannot read files packed by newer versions (GH12129, GH10527)

Bugs in `to_msgpack` and `read_msgpack` introduced in 0.17.0 and fixed in 0.18.0, caused files packed in Python 2 unreadable by Python 3 (GH12142). The following table describes the backward and forward compat of msgpacks.

Warning:

Packed with	Can be unpacked with
pre-0.17 / Python 2	any
pre-0.17 / Python 3	any
0.17 / Python 2	• ==0.17 / Python 2 • >=0.18 / any Python
0.17 / Python 3	>=0.18 / any Python
0.18	>= 0.18

0.18.0 is backward-compatible for reading files packed by older versions, except for files packed with 0.17 in Python 2, in which case only they can only be unpacked in Python 2.

Signature change for .rank

`Series.rank` and `DataFrame.rank` now have the same signature (GH11759)

Previous signature

```
In [3]: pd.Series([0,1]).rank(method='average', na_option='keep',
                              ascending=True, pct=False)
Out[3]:
0    1
1    2
dtype: float64

In [4]: pd.DataFrame([0,1]).rank(axis=0, numeric_only=None,
                                 method='average', na_option='keep',
                                 ascending=True, pct=False)
Out[4]:
   0
0  1
1  2
```

New signature

```
In [71]: pd.Series([0,1]).rank(axis=0, method='average', numeric_only=None,
   ....:                        na_option='keep', ascending=True, pct=False)
   ....:
Out[71]:
0    1.0
1    2.0
Length: 2, dtype: float64

In [72]: pd.DataFrame([0,1]).rank(axis=0, method='average', numeric_only=None,
   ....:                          na_option='keep', ascending=True, pct=False)
   ....:
Out[72]:
     0
0  1.0
1  2.0

[2 rows x 1 columns]
```

Bug in QuarterBegin with n=0

In previous versions, the behavior of the QuarterBegin offset was inconsistent depending on the date when the `n` parameter was 0. (GH11406)

The general semantics of anchored offsets for `n=0` is to not move the date when it is an anchor point (e.g., a quarter start date), and otherwise roll forward to the next anchor point.

```
In [73]: d = pd.Timestamp('2014-02-01')

In [74]: d
Out[74]: Timestamp('2014-02-01 00:00:00')

In [75]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[75]: Timestamp('2014-02-01 00:00:00')

In [76]: d + pd.offsets.QuarterBegin(n=0, startingMonth=1)
Out[76]: Timestamp('2014-04-01 00:00:00')
```

For the `QuarterBegin` offset in previous versions, the date would be rolled *backwards* if date was in the same month as the quarter start date.

```
In [3]: d = pd.Timestamp('2014-02-15')

In [4]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[4]: Timestamp('2014-02-01 00:00:00')
```

This behavior has been corrected in version 0.18.0, which is consistent with other anchored offsets like `MonthBegin` and `YearBegin`.

```
In [77]: d = pd.Timestamp('2014-02-15')

In [78]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[78]: Timestamp('2014-05-01 00:00:00')
```

Resample API

Like the change in the window functions API *above*, `.resample(...)` is changing to have a more groupby-like API. (GH11732, GH12702, GH12202, GH12332, GH12334, GH12348, GH12448).

```
In [79]: np.random.seed(1234)

In [80]: df = pd.DataFrame(np.random.rand(10,4),
   ....:                   columns=list('ABCD'),
   ....:                   index=pd.date_range('2010-01-01 09:00:00',
   ....:                                       periods=10, freq='s'))
   ....:

In [81]: df
Out[81]:
                            A         B         C         D
2010-01-01 09:00:00  0.191519  0.622109  0.437728  0.785359
2010-01-01 09:00:01  0.779976  0.272593  0.276464  0.801872
2010-01-01 09:00:02  0.958139  0.875933  0.357817  0.500995
2010-01-01 09:00:03  0.683463  0.712702  0.370251  0.561196
2010-01-01 09:00:04  0.503083  0.013768  0.772827  0.882641
2010-01-01 09:00:05  0.364886  0.615396  0.075381  0.368824
2010-01-01 09:00:06  0.933140  0.651378  0.397203  0.788730
2010-01-01 09:00:07  0.316836  0.568099  0.869127  0.436173
2010-01-01 09:00:08  0.802148  0.143767  0.704261  0.704581
2010-01-01 09:00:09  0.218792  0.924868  0.442141  0.909316

[10 rows x 4 columns]
```

Previous API:

You would write a resampling operation that immediately evaluates. If a `how` parameter was not provided, it would default to `how='mean'`.

```
In [6]: df.resample('2s')
Out[6]:
                            A         B         C         D
2010-01-01 09:00:00  0.485748  0.447351  0.357096  0.793615
2010-01-01 09:00:02  0.820801  0.794317  0.364034  0.531096
2010-01-01 09:00:04  0.433985  0.314582  0.424104  0.625733
2010-01-01 09:00:06  0.624988  0.609738  0.633165  0.612452
2010-01-01 09:00:08  0.510470  0.534317  0.573201  0.806949
```

You could also specify a `how` directly

```
In [7]: df.resample('2s', how='sum')
Out[7]:
                            A         B         C         D
2010-01-01 09:00:00  0.971495  0.894701  0.714192  1.587231
2010-01-01 09:00:02  1.641602  1.588635  0.728068  1.062191
2010-01-01 09:00:04  0.867969  0.629165  0.848208  1.251465
2010-01-01 09:00:06  1.249976  1.219477  1.266330  1.224904
2010-01-01 09:00:08  1.020940  1.068634  1.146402  1.613897
```

New API:

Now, you can write `.resample(..)` as a 2-stage operation like `.groupby(...)`, which yields a `Resampler`.

```
In [82]: r = df.resample('2s')

In [83]: r
Out[83]: <pandas.core.resample.DatetimeIndexResampler object at 0x7f708c0d5a00>
```

Downsampling

You can then use this object to perform operations. These are downsampling operations (going from a higher frequency to a lower one).

```
In [84]: r.mean()
Out[84]:
                            A         B         C         D
2010-01-01 09:00:00  0.485748  0.447351  0.357096  0.793615
2010-01-01 09:00:02  0.820801  0.794317  0.364034  0.531096
2010-01-01 09:00:04  0.433985  0.314582  0.424104  0.625733
2010-01-01 09:00:06  0.624988  0.609738  0.633165  0.612452
2010-01-01 09:00:08  0.510470  0.534317  0.573201  0.806949

[5 rows x 4 columns]
```

```
In [85]: r.sum()
Out[85]:
                            A         B         C         D
2010-01-01 09:00:00  0.971495  0.894701  0.714192  1.587231
2010-01-01 09:00:02  1.641602  1.588635  0.728068  1.062191
2010-01-01 09:00:04  0.867969  0.629165  0.848208  1.251465
```

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```
2010-01-01 09:00:06  1.249976  1.219477  1.266330  1.224904
2010-01-01 09:00:08  1.020940  1.068634  1.146402  1.613897

[5 rows x 4 columns]
```

Furthermore, resample now supports `getitem` operations to perform the resample on specific columns.

```
In [86]: r[['A','C']].mean()
Out[86]:
                            A         C
2010-01-01 09:00:00  0.485748  0.357096
2010-01-01 09:00:02  0.820801  0.364034
2010-01-01 09:00:04  0.433985  0.424104
2010-01-01 09:00:06  0.624988  0.633165
2010-01-01 09:00:08  0.510470  0.573201

[5 rows x 2 columns]
```

and `.aggregate` type operations.

```
In [87]: r.agg({'A' : 'mean', 'B' : 'sum'})
Out[87]:
                            A         B
2010-01-01 09:00:00  0.485748  0.894701
2010-01-01 09:00:02  0.820801  1.588635
2010-01-01 09:00:04  0.433985  0.629165
2010-01-01 09:00:06  0.624988  1.219477
2010-01-01 09:00:08  0.510470  1.068634

[5 rows x 2 columns]
```

These accessors can of course, be combined

```
In [88]: r[['A','B']].agg(['mean','sum'])
Out[88]:
                            A                   B
                         mean       sum      mean       sum
2010-01-01 09:00:00  0.485748  0.971495  0.447351  0.894701
2010-01-01 09:00:02  0.820801  1.641602  0.794317  1.588635
2010-01-01 09:00:04  0.433985  0.867969  0.314582  0.629165
2010-01-01 09:00:06  0.624988  1.249976  0.609738  1.219477
2010-01-01 09:00:08  0.510470  1.020940  0.534317  1.068634

[5 rows x 4 columns]
```

Upsampling

Upsampling operations take you from a lower frequency to a higher frequency. These are now performed with the `Resampler` objects with `backfill()`, `ffill()`, `fillna()` and `asfreq()` methods.

```
In [89]: s = pd.Series(np.arange(5, dtype='int64'),
   ....:               index=pd.date_range('2010-01-01', periods=5, freq='Q'))
   ....:

In [90]: s
```

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```
Out[90]:
2010-03-31    0
2010-06-30    1
2010-09-30    2
2010-12-31    3
2011-03-31    4
Freq: Q-DEC, Length: 5, dtype: int64
```

Previously

```
In [6]: s.resample('M', fill_method='ffill')
Out[6]:
2010-03-31    0
2010-04-30    0
2010-05-31    0
2010-06-30    1
2010-07-31    1
2010-08-31    1
2010-09-30    2
2010-10-31    2
2010-11-30    2
2010-12-31    3
2011-01-31    3
2011-02-28    3
2011-03-31    4
Freq: M, dtype: int64
```

New API

```
In [91]: s.resample('M').ffill()
Out[91]:
2010-03-31    0
2010-04-30    0
2010-05-31    0
2010-06-30    1
2010-07-31    1
2010-08-31    1
2010-09-30    2
2010-10-31    2
2010-11-30    2
2010-12-31    3
2011-01-31    3
2011-02-28    3
2011-03-31    4
Freq: M, Length: 13, dtype: int64
```

Note: In the new API, you can either downsample OR upsample. The prior implementation would allow you to pass an aggregator function (like `mean`) even though you were upsampling, providing a bit of confusion.

Previous API will work but with deprecations

Warning: This new API for resample includes some internal changes for the prior-to-0.18.0 API, to work with a deprecation warning in most cases, as the resample operation returns a deferred object. We can intercept operations and just do what the (pre 0.18.0) API did (with a warning). Here is a typical use case:

```
In [4]: r = df.resample('2s')

In [6]: r*10
pandas/tseries/resample.py:80: FutureWarning: .resample() is now a deferred␣
↪operation
use .resample(...).mean() instead of .resample(...)

Out[6]:
                            A         B         C         D
2010-01-01 09:00:00  4.857476  4.473507  3.570960  7.936154
2010-01-01 09:00:02  8.208011  7.943173  3.640340  5.310957
2010-01-01 09:00:04  4.339846  3.145823  4.241039  6.257326
2010-01-01 09:00:06  6.249881  6.097384  6.331650  6.124518
2010-01-01 09:00:08  5.104699  5.343172  5.732009  8.069486
```

However, getting and assignment operations directly on a `Resampler` will raise a `ValueError`:

```
In [7]: r.iloc[0] = 5
ValueError: .resample() is now a deferred operation
use .resample(...).mean() instead of .resample(...)
```

There is a situation where the new API can not perform all the operations when using original code. This code is intending to resample every 2s, take the `mean` AND then take the `min` of those results.

```
In [4]: df.resample('2s').min()
Out[4]:
A    0.433985
B    0.314582
C    0.357096
D    0.531096
dtype: float64
```

The new API will:

```
In [92]: df.resample('2s').min()
Out[92]:
                               A         B         C         D
2010-01-01 09:00:00  0.191519  0.272593  0.276464  0.785359
2010-01-01 09:00:02  0.683463  0.712702  0.357817  0.500995
2010-01-01 09:00:04  0.364886  0.013768  0.075381  0.368824
2010-01-01 09:00:06  0.316836  0.568099  0.397203  0.436173
2010-01-01 09:00:08  0.218792  0.143767  0.442141  0.704581

[5 rows x 4 columns]
```

The good news is the return dimensions will differ between the new API and the old API, so this should loudly raise an exception.

To replicate the original operation

```
In [93]: df.resample('2s').mean().min()
Out[93]:
A    0.433985
B    0.314582
C    0.357096
D    0.531096
Length: 4, dtype: float64
```

Changes to eval

In prior versions, new columns assignments in an `eval` expression resulted in an inplace change to the `DataFrame`. (GH9297, GH8664, GH10486)

```
In [94]: df = pd.DataFrame({'a': np.linspace(0, 10, 5), 'b': range(5)})

In [95]: df
Out[95]:
      a  b
0   0.0  0
1   2.5  1
2   5.0  2
3   7.5  3
4  10.0  4

[5 rows x 2 columns]
```

```
In [12]: df.eval('c = a + b')
FutureWarning: eval expressions containing an assignment currentlydefault to␣
↪operating inplace.
This will change in a future version of pandas, use inplace=True to avoid this␣
↪warning.

In [13]: df
Out[13]:
      a  b     c
0   0.0  0   0.0
1   2.5  1   3.5
2   5.0  2   7.0
3   7.5  3  10.5
4  10.0  4  14.0
```

In version 0.18.0, a new `inplace` keyword was added to choose whether the assignment should be done inplace or return a copy.

```
In [96]: df
Out[96]:
      a  b     c
0   0.0  0   0.0
1   2.5  1   3.5
2   5.0  2   7.0
3   7.5  3  10.5
4  10.0  4  14.0

[5 rows x 3 columns]

In [97]: df.eval('d = c - b', inplace=False)
Out[97]:
      a  b     c     d
0   0.0  0   0.0   0.0
1   2.5  1   3.5   2.5
2   5.0  2   7.0   5.0
```

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```
3   7.5  3  10.5   7.5
4  10.0  4  14.0  10.0

[5 rows x 4 columns]

In [98]: df
Out[98]:
      a  b     c
0   0.0  0   0.0
1   2.5  1   3.5
2   5.0  2   7.0
3   7.5  3  10.5
4  10.0  4  14.0

[5 rows x 3 columns]

In [99]: df.eval('d = c - b', inplace=True)

In [100]: df
Out[100]:
      a  b     c     d
0   0.0  0   0.0   0.0
1   2.5  1   3.5   2.5
2   5.0  2   7.0   5.0
3   7.5  3  10.5   7.5
4  10.0  4  14.0  10.0

[5 rows x 4 columns]
```

Warning: For backwards compatibility, `inplace` defaults to `True` if not specified. This will change in a future version of pandas. If your code depends on an inplace assignment you should update to explicitly set `inplace=True`

The `inplace` keyword parameter was also added the `query` method.

```
In [101]: df.query('a > 5')
Out[101]:
      a  b     c     d
3   7.5  3  10.5   7.5
4  10.0  4  14.0  10.0

[2 rows x 4 columns]

In [102]: df.query('a > 5', inplace=True)

In [103]: df
Out[103]:
      a  b     c     d
3   7.5  3  10.5   7.5
4  10.0  4  14.0  10.0

[2 rows x 4 columns]
```

Warning: Note that the default value for `inplace` in a `query` is `False`, which is consistent with prior versions.

`eval` has also been updated to allow multi-line expressions for multiple assignments. These expressions will be evaluated one at a time in order. Only assignments are valid for multi-line expressions.

```
In [104]: df
Out[104]:
      a  b     c     d
3   7.5  3  10.5   7.5
4  10.0  4  14.0  10.0

[2 rows x 4 columns]

In [105]: df.eval("""
   .....: e = d + a
   .....: f = e - 22
   .....: g = f / 2.0""", inplace=True)
   .....:

In [106]: df
Out[106]:
      a  b     c     d     e    f    g
3   7.5  3  10.5   7.5  15.0 -7.0 -3.5
4  10.0  4  14.0  10.0  20.0 -2.0 -1.0

[2 rows x 7 columns]
```

Other API changes

- `DataFrame.between_time` and `Series.between_time` now only parse a fixed set of time strings. Parsing of date strings is no longer supported and raises a `ValueError`. (GH11818)

```
In [107]: s = pd.Series(range(10), pd.date_range('2015-01-01', freq='H',␣
↪periods=10))

In [108]: s.between_time("7:00am", "9:00am")
Out[108]:
2015-01-01 07:00:00    7
2015-01-01 08:00:00    8
2015-01-01 09:00:00    9
Freq: H, Length: 3, dtype: int64
```

  This will now raise.

```
In [2]: s.between_time('20150101 07:00:00','20150101 09:00:00')
ValueError: Cannot convert arg ['20150101 07:00:00'] to a time.
```

- `.memory_usage()` now includes values in the index, as does memory_usage in `.info()` (GH11597)
- `DataFrame.to_latex()` now supports non-ascii encodings (eg `utf-8`) in Python 2 with the parameter `encoding` (GH7061)
- `pandas.merge()` and `DataFrame.merge()` will show a specific error message when trying to merge with an object that is not of type `DataFrame` or a subclass (GH12081)

- `DataFrame.unstack` and `Series.unstack` now take `fill_value` keyword to allow direct replacement of missing values when an unstack results in missing values in the resulting `DataFrame`. As an added benefit, specifying `fill_value` will preserve the data type of the original stacked data. (GH9746)
- As part of the new API for *window functions* and *resampling*, aggregation functions have been clarified, raising more informative error messages on invalid aggregations. (GH9052). A full set of examples are presented in *groupby*.
- Statistical functions for `NDFrame` objects (like `sum(), mean(), min()`) will now raise if non-numpy-compatible arguments are passed in for `**kwargs` (GH12301)
- `.to_latex` and `.to_html` gain a `decimal` parameter like `.to_csv`; the default is `'.'` (GH12031)
- More helpful error message when constructing a `DataFrame` with empty data but with indices (GH8020)
- `.describe()` will now properly handle bool dtype as a categorical (GH6625)
- More helpful error message with an invalid `.transform` with user defined input (GH10165)
- Exponentially weighted functions now allow specifying alpha directly (GH10789) and raise `ValueError` if parameters violate `0 < alpha <= 1` (GH12492)

Deprecations

- The functions `pd.rolling_*`, `pd.expanding_*`, and `pd.ewm*` are deprecated and replaced by the corresponding method call. Note that the new suggested syntax includes all of the arguments (even if default) (GH11603)

```
In [1]: s = pd.Series(range(3))

In [2]: pd.rolling_mean(s,window=2,min_periods=1)
        FutureWarning: pd.rolling_mean is deprecated for Series and
             will be removed in a future version, replace with
             Series.rolling(min_periods=1,window=2,center=False).mean()
Out[2]:
        0    0.0
        1    0.5
        2    1.5
        dtype: float64

In [3]: pd.rolling_cov(s, s, window=2)
        FutureWarning: pd.rolling_cov is deprecated for Series and
             will be removed in a future version, replace with
             Series.rolling(window=2).cov(other=<Series>)
Out[3]:
        0    NaN
        1    0.5
        2    0.5
        dtype: float64
```

- The `freq` and `how` arguments to the `.rolling`, `.expanding`, and `.ewm` (new) functions are deprecated, and will be removed in a future version. You can simply resample the input prior to creating a window function. (GH11603).

  For example, instead of `s.rolling(window=5,freq='D').max()` to get the max value on a rolling 5 Day window, one could use `s.resample('D').mean().rolling(window=5).max()`, which first resamples the data to daily data, then provides a rolling 5 day window.

- `pd.tseries.frequencies.get_offset_name` function is deprecated. Use offset's `.freqstr` property as alternative (GH11192)
- `pandas.stats.fama_macbeth` routines are deprecated and will be removed in a future version (GH6077)
- `pandas.stats.ols`, `pandas.stats.plm` and `pandas.stats.var` routines are deprecated and will be removed in a future version (GH6077)
- show a `FutureWarning` rather than a `DeprecationWarning` on using long-time deprecated syntax in `HDFStore.select`, where the `where` clause is not a string-like (GH12027)
- The `pandas.options.display.mpl_style` configuration has been deprecated and will be removed in a future version of pandas. This functionality is better handled by matplotlib's style sheets (GH11783).

Removal of deprecated float indexers

In GH4892 indexing with floating point numbers on a non-`Float64Index` was deprecated (in version 0.14.0). In 0.18.0, this deprecation warning is removed and these will now raise a `TypeError`. (GH12165, GH12333)

```
In [109]: s = pd.Series([1, 2, 3], index=[4, 5, 6])

In [110]: s
Out[110]:
4    1
5    2
6    3
Length: 3, dtype: int64

In [111]: s2 = pd.Series([1, 2, 3], index=list('abc'))

In [112]: s2
Out[112]:
a    1
b    2
c    3
Length: 3, dtype: int64
```

Previous behavior:

```
# this is label indexing
In [2]: s[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not␣
↪floating point
Out[2]: 2

# this is positional indexing
In [3]: s.iloc[1.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not␣
↪floating point
Out[3]: 2

# this is label indexing
In [4]: s.loc[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not␣
↪floating point
Out[4]: 2

# .ix would coerce 1.0 to the positional 1, and index
```

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```
In [5]: s2.ix[1.0] = 10
FutureWarning: scalar indexers for index type Index should be integers and not␣
↪floating point

In [6]: s2
Out[6]:
a     1
b    10
c     3
dtype: int64
```

New behavior:

For iloc, getting & setting via a float scalar will always raise.

```
In [3]: s.iloc[2.0]
TypeError: cannot do label indexing on <class 'pandas.indexes.numeric.Int64Index'>␣
↪with these indexers [2.0] of <type 'float'>
```

Other indexers will coerce to a like integer for both getting and setting. The `FutureWarning` has been dropped for `.loc`, `.ix` and `[]`.

```
In [113]: s[5.0]
Out[113]: 2

In [114]: s.loc[5.0]
Out[114]: 2
```

and setting

```
In [115]: s_copy = s.copy()

In [116]: s_copy[5.0] = 10

In [117]: s_copy
Out[117]:
4     1
5    10
6     3
Length: 3, dtype: int64

In [118]: s_copy = s.copy()

In [119]: s_copy.loc[5.0] = 10

In [120]: s_copy
Out[120]:
4     1
5    10
6     3
Length: 3, dtype: int64
```

Positional setting with `.ix` and a float indexer will ADD this value to the index, rather than previously setting the value by position.

```
In [3]: s2.ix[1.0] = 10
In [4]: s2
```

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```
Out[4]:
a       1
b       2
c       3
1.0    10
dtype: int64
```

Slicing will also coerce integer-like floats to integers for a non-`Float64Index`.

```
In [121]: s.loc[5.0:6]
Out[121]:
5    2
6    3
Length: 2, dtype: int64
```

Note that for floats that are NOT coercible to ints, the label based bounds will be excluded

```
In [122]: s.loc[5.1:6]
Out[122]:
6    3
Length: 1, dtype: int64
```

Float indexing on a `Float64Index` is unchanged.

```
In [123]: s = pd.Series([1, 2, 3], index=np.arange(3.))

In [124]: s[1.0]
Out[124]: 2

In [125]: s[1.0:2.5]
Out[125]:
1.0    2
2.0    3
Length: 2, dtype: int64
```

Removal of prior version deprecations/changes

- Removal of `rolling_corr_pairwise` in favor of `.rolling().corr(pairwise=True)` (GH4950)
- Removal of `expanding_corr_pairwise` in favor of `.expanding().corr(pairwise=True)` (GH4950)
- Removal of `DataMatrix` module. This was not imported into the pandas namespace in any event (GH12111)
- Removal of `cols` keyword in favor of `subset` in `DataFrame.duplicated()` and `DataFrame.drop_duplicates()` (GH6680)
- Removal of the `read_frame` and `frame_query` (both aliases for `pd.read_sql`) and `write_frame` (alias of `to_sql`) functions in the `pd.io.sql` namespace, deprecated since 0.14.0 (GH6292).
- Removal of the `order` keyword from `.factorize()` (GH6930)

Performance improvements

- Improved performance of `andrews_curves` (GH11534)
- Improved huge `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex`'s ops performance including `NaT` (GH10277)
- Improved performance of `pandas.concat` (GH11958)
- Improved performance of `StataReader` (GH11591)
- Improved performance in construction of `Categoricals` with `Series` of datetimes containing `NaT` (GH12077)
- Improved performance of ISO 8601 date parsing for dates without separators (GH11899), leading zeros (GH11871) and with white space preceding the time zone (GH9714)

Bug fixes

- Bug in `GroupBy.size` when data-frame is empty. (GH11699)
- Bug in `Period.end_time` when a multiple of time period is requested (GH11738)
- Regression in `.clip` with tz-aware datetimes (GH11838)
- Bug in `date_range` when the boundaries fell on the frequency (GH11804, GH12409)
- Bug in consistency of passing nested dicts to `.groupby(...).agg(...)` (GH9052)
- Accept unicode in `Timedelta` constructor (GH11995)
- Bug in value label reading for `StataReader` when reading incrementally (GH12014)
- Bug in vectorized `DateOffset` when `n` parameter is `0` (GH11370)
- Compat for numpy 1.11 w.r.t. `NaT` comparison changes (GH12049)
- Bug in `read_csv` when reading from a `StringIO` in threads (GH11790)
- Bug in not treating `NaT` as a missing value in datetimelikes when factorizing & with `Categoricals` (GH12077)
- Bug in getitem when the values of a `Series` were tz-aware (GH12089)
- Bug in `Series.str.get_dummies` when one of the variables was 'name' (GH12180)
- Bug in `pd.concat` while concatenating tz-aware NaT series. (GH11693, GH11755, GH12217)
- Bug in `pd.read_stata` with version <= 108 files (GH12232)
- Bug in `Series.resample` using a frequency of `Nano` when the index is a `DatetimeIndex` and contains non-zero nanosecond parts (GH12037)
- Bug in resampling with `.nunique` and a sparse index (GH12352)
- Removed some compiler warnings (GH12471)
- Work around compat issues with `boto` in python 3.5 (GH11915)
- Bug in `NaT` subtraction from `Timestamp` or `DatetimeIndex` with timezones (GH11718)
- Bug in subtraction of `Series` of a single tz-aware `Timestamp` (GH12290)
- Use compat iterators in PY2 to support `.next()` (GH12299)
- Bug in `Timedelta.round` with negative values (GH11690)

- Bug in `.loc` against `CategoricalIndex` may result in normal `Index` (GH11586)
- Bug in `DataFrame.info` when duplicated column names exist (GH11761)
- Bug in `.copy` of datetime tz-aware objects (GH11794)
- Bug in `Series.apply` and `Series.map` where `timedelta64` was not boxed (GH11349)
- Bug in `DataFrame.set_index()` with tz-aware `Series` (GH12358)
- Bug in subclasses of `DataFrame` where `AttributeError` did not propagate (GH11808)
- Bug groupby on tz-aware data where selection not returning `Timestamp` (GH11616)
- Bug in `pd.read_clipboard` and `pd.to_clipboard` functions not supporting Unicode; upgrade included `pyperclip` to v1.5.15 (GH9263)
- Bug in `DataFrame.query` containing an assignment (GH8664)
- Bug in `from_msgpack` where `__contains__()` fails for columns of the unpacked `DataFrame`, if the `DataFrame` has object columns. (GH11880)
- Bug in `.resample` on categorical data with `TimedeltaIndex` (GH12169)
- Bug in timezone info lost when broadcasting scalar datetime to `DataFrame` (GH11682)
- Bug in `Index` creation from `Timestamp` with mixed tz coerces to UTC (GH11488)
- Bug in `to_numeric` where it does not raise if input is more than one dimension (GH11776)
- Bug in parsing timezone offset strings with non-zero minutes (GH11708)
- Bug in `df.plot` using incorrect colors for bar plots under matplotlib 1.5+ (GH11614)
- Bug in the `groupby plot` method when using keyword arguments (GH11805).
- Bug in `DataFrame.duplicated` and `drop_duplicates` causing spurious matches when setting `keep=False` (GH11864)
- Bug in `.loc` result with duplicated key may have `Index` with incorrect dtype (GH11497)
- Bug in `pd.rolling_median` where memory allocation failed even with sufficient memory (GH11696)
- Bug in `DataFrame.style` with spurious zeros (GH12134)
- Bug in `DataFrame.style` with integer columns not starting at 0 (GH12125)
- Bug in `.style.bar` may not rendered properly using specific browser (GH11678)
- Bug in rich comparison of `Timedelta` with a `numpy.array` of `Timedelta` that caused an infinite recursion (GH11835)
- Bug in `DataFrame.round` dropping column index name (GH11986)
- Bug in `df.replace` while replacing value in mixed dtype `Dataframe` (GH11698)
- Bug in `Index` prevents copying name of passed `Index`, when a new name is not provided (GH11193)
- Bug in `read_excel` failing to read any non-empty sheets when empty sheets exist and `sheetname=None` (GH11711)
- Bug in `read_excel` failing to raise `NotImplemented` error when keywords `parse_dates` and `date_parser` are provided (GH11544)
- Bug in `read_sql` with `pymysql` connections failing to return chunked data (GH11522)
- Bug in `.to_csv` ignoring formatting parameters `decimal`, `na_rep`, `float_format` for float indexes (GH11553)

- Bug in `Int64Index` and `Float64Index` preventing the use of the modulo operator (GH9244)
- Bug in `MultiIndex.drop` for not lexsorted MultiIndexes (GH12078)
- Bug in `DataFrame` when masking an empty `DataFrame` (GH11859)
- Bug in `.plot` potentially modifying the `colors` input when the number of columns didn't match the number of series provided (GH12039).
- Bug in `Series.plot` failing when index has a `CustomBusinessDay` frequency (GH7222).
- Bug in `.to_sql` for `datetime.time` values with sqlite fallback (GH8341)
- Bug in `read_excel` failing to read data with one column when `squeeze=True` (GH12157)
- Bug in `read_excel` failing to read one empty column (GH12292, GH9002)
- Bug in `.groupby` where a `KeyError` was not raised for a wrong column if there was only one row in the dataframe (GH11741)
- Bug in `.read_csv` with dtype specified on empty data producing an error (GH12048)
- Bug in `.read_csv` where strings like `'2E'` are treated as valid floats (GH12237)
- Bug in building *pandas* with debugging symbols (GH12123)
- Removed `millisecond` property of `DatetimeIndex`. This would always raise a `ValueError` (GH12019).
- Bug in `Series` constructor with read-only data (GH11502)
- Removed `pandas._testing.choice()`. Should use `np.random.choice()`, instead. (GH12386)
- Bug in `.loc` setitem indexer preventing the use of a TZ-aware DatetimeIndex (GH12050)
- Bug in `.style` indexes and MultiIndexes not appearing (GH11655)
- Bug in `to_msgpack` and `from_msgpack` which did not correctly serialize or deserialize `NaT` (GH12307).
- Bug in `.skew` and `.kurt` due to roundoff error for highly similar values (GH11974)
- Bug in `Timestamp` constructor where microsecond resolution was lost if HHMMSS were not separated with ':' (GH10041)
- Bug in `buffer_rd_bytes` src->buffer could be freed more than once if reading failed, causing a segfault (GH12098)
- Bug in `crosstab` where arguments with non-overlapping indexes would return a `KeyError` (GH10291)
- Bug in `DataFrame.apply` in which reduction was not being prevented for cases in which `dtype` was not a numpy dtype (GH12244)
- Bug when initializing categorical series with a scalar value. (GH12336)
- Bug when specifying a UTC `DatetimeIndex` by setting `utc=True` in `.to_datetime` (GH11934)
- Bug when increasing the buffer size of CSV reader in `read_csv` (GH12494)
- Bug when setting columns of a `DataFrame` with duplicate column names (GH12344)

Contributors

A total of 101 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- dgram0 +
- gfyoung +
- hack-c +
- hcontrast +
- jfoo +
- kaustuv deolal +
- lllllllll
- ranarag +
- rockg
- scls19fr
- seales +
- sinhrks
- srib +
- surveymedia.ca +
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5.12 Version 0.17

5.12.1 Version 0.17.1 (November 21, 2015)

Note: We are proud to announce that *pandas* has become a sponsored project of the (NumFOCUS organization). This will help ensure the success of development of *pandas* as a world-class open-source project.

This is a minor bug-fix release from 0.17.0 and includes a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Support for Conditional HTML Formatting, see *here*
- Releasing the GIL on the csv reader & other ops, see *here*
- Fixed regression in `DataFrame.drop_duplicates` from 0.16.2, causing incorrect results on integer values (GH11376)

What's new in v0.17.1

- *New features*
  - *Conditional HTML formatting*
- *Enhancements*
- *API changes*
  - *Deprecations*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

New features

Conditional HTML formatting

Warning: This is a new feature and is under active development. We'll be adding features an possibly making breaking changes in future releases. Feedback is welcome.

We've added *experimental* support for conditional HTML formatting: the visual styling of a DataFrame based on the data. The styling is accomplished with HTML and CSS. Accesses the styler class with the *`pandas.DataFrame.style`*, attribute, an instance of `Styler` with your data attached.

Here's a quick example:

```
In [1]: np.random.seed(123)

In [2]: df = pd.DataFrame(np.random.randn(10, 5), columns=list("abcde"))
```

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```
In [3]: html = df.style.background_gradient(cmap="viridis", low=0.5)
```

We can render the HTML to get the following table.

`Styler` interacts nicely with the Jupyter Notebook. See the *documentation* for more.

Enhancements

- `DatetimeIndex` now supports conversion to strings with `astype(str)` (GH10442)
- Support for `compression` (gzip/bz2) in *`pandas.DataFrame.to_csv()`* (GH7615)
- `pd.read_*` functions can now also accept `pathlib.Path`, or `py._path.local.LocalPath` objects for the `filepath_or_buffer` argument. (GH11033) - The `DataFrame` and `Series` functions `.to_csv()`, `.to_html()` and `.to_latex()` can now handle paths beginning with tildes (e.g. `~/Documents/`) (GH11438)
- `DataFrame` now uses the fields of a `namedtuple` as columns, if columns are not supplied (GH11181)
- `DataFrame.itertuples()` now returns `namedtuple` objects, when possible. (GH11269, GH11625)
- Added `axvlines_kwds` to parallel coordinates plot (GH10709)
- Option to `.info()` and `.memory_usage()` to provide for deep introspection of memory consumption. Note that this can be expensive to compute and therefore is an optional parameter. (GH11595)

```
In [4]: df = pd.DataFrame({"A": ["foo"] * 1000})  # noqa: F821

In [5]: df["B"] = df["A"].astype("category")

# shows the '+' as we have object dtypes
In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   A       1000 non-null   object
 1   B       1000 non-null   category
dtypes: category(1), object(1)
memory usage: 9.0+ KB

# we have an accurate memory assessment (but can be expensive to compute this)
In [7]: df.info(memory_usage="deep")
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   A       1000 non-null   object
 1   B       1000 non-null   category
dtypes: category(1), object(1)
memory usage: 59.9 KB
```

- `Index` now has a `fillna` method (GH10089)

```
In [8]: pd.Index([1, np.nan, 3]).fillna(2)
Out[8]: Float64Index([1.0, 2.0, 3.0], dtype='float64')
```

- Series of type `category` now make `.str.<...>` and `.dt.<...>` accessor methods / properties available, if the categories are of that type. (GH10661)

```
In [9]: s = pd.Series(list("aabb")).astype("category")

In [10]: s
Out[10]:
0    a
1    a
2    b
3    b
Length: 4, dtype: category
Categories (2, object): ['a', 'b']

In [11]: s.str.contains("a")
Out[11]:
0     True
1     True
2    False
3    False
Length: 4, dtype: bool

In [12]: date = pd.Series(pd.date_range("1/1/2015", periods=5)).astype("category")

In [13]: date
Out[13]:
0   2015-01-01
1   2015-01-02
2   2015-01-03
3   2015-01-04
4   2015-01-05
Length: 5, dtype: category
Categories (5, datetime64[ns]): [2015-01-01, 2015-01-02, 2015-01-03, 2015-01-04,␣
↪2015-01-05]

In [14]: date.dt.day
Out[14]:
0    1
1    2
2    3
3    4
4    5
Length: 5, dtype: int64
```

- `pivot_table` now has a `margins_name` argument so you can use something other than the default of 'All' (GH3335)
- Implement export of `datetime64[ns, tz]` dtypes with a fixed HDF5 store (GH11411)
- Pretty printing sets (e.g. in DataFrame cells) now uses set literal syntax (`{x, y}`) instead of Legacy Python syntax (`set([x, y])`) (GH11215)
- Improve the error message in `pandas.io.gbq.to_gbq()` when a streaming insert fails (GH11285) and when the DataFrame does not match the schema of the destination table (GH11359)

API changes

- raise `NotImplementedError` in `Index.shift` for non-supported index types (GH8038)
- `min` and `max` reductions on `datetime64` and `timedelta64` dtyped series now result in `NaT` and not `nan` (GH11245).
- Indexing with a null key will raise a `TypeError`, instead of a `ValueError` (GH11356)
- `Series.ptp` will now ignore missing values by default (GH11163)

Deprecations

- The `pandas.io.ga` module which implements `google-analytics` support is deprecated and will be removed in a future version (GH11308)
- Deprecate the `engine` keyword in `.to_csv()`, which will be removed in a future version (GH11274)

Performance improvements

- Checking monotonic-ness before sorting on an index (GH11080)
- `Series.dropna` performance improvement when its dtype can't contain `NaN` (GH11159)
- Release the GIL on most datetime field operations (e.g. `DatetimeIndex.year`, `Series.dt.year`), normalization, and conversion to and from `Period`, `DatetimeIndex.to_period` and `PeriodIndex.to_timestamp` (GH11263)
- Release the GIL on some rolling algos: `rolling_median`, `rolling_mean`, `rolling_max`, `rolling_min`, `rolling_var`, `rolling_kurt`, `rolling_skew` (GH11450)
- Release the GIL when reading and parsing text files in `read_csv`, `read_table` (GH11272)
- Improved performance of `rolling_median` (GH11450)
- Improved performance of `to_excel` (GH11352)
- Performance bug in repr of `Categorical` categories, which was rendering the strings before chopping them for display (GH11305)
- Performance improvement in `Categorical.remove_unused_categories`, (GH11643).
- Improved performance of `Series` constructor with no data and `DatetimeIndex` (GH11433)
- Improved performance of `shift`, `cumprod`, and `cumsum` with groupby (GH4095)

Bug fixes

- `SparseArray.__iter__()` now does not cause `PendingDeprecationWarning` in Python 3.5 (GH11622)
- Regression from 0.16.2 for output formatting of long floats/nan, restored in (GH11302)
- `Series.sort_index()` now correctly handles the `inplace` option (GH11402)
- Incorrectly distributed .c file in the build on `PyPi` when reading a csv of floats and passing `na_values=<a scalar>` would show an exception (GH11374)
- Bug in `.to_latex()` output broken when the index has a name (GH10660)

- Bug in `HDFStore.append` with strings whose encoded length exceeded the max unencoded length (GH11234)
- Bug in merging `datetime64[ns, tz]` dtypes (GH11405)
- Bug in `HDFStore.select` when comparing with a numpy scalar in a where clause (GH11283)
- Bug in using `DataFrame.ix` with a MultiIndex indexer (GH11372)
- Bug in `date_range` with ambiguous endpoints (GH11626)
- Prevent adding new attributes to the accessors `.str`, `.dt` and `.cat`. Retrieving such a value was not possible, so error out on setting it. (GH10673)
- Bug in tz-conversions with an ambiguous time and `.dt` accessors (GH11295)
- Bug in output formatting when using an index of ambiguous times (GH11619)
- Bug in comparisons of Series vs list-likes (GH11339)
- Bug in `DataFrame.replace` with a `datetime64[ns, tz]` and a non-compat to_replace (GH11326, GH11153)
- Bug in `isnull` where `numpy.datetime64('NaT')` in a `numpy.array` was not determined to be null(GH11206)
- Bug in list-like indexing with a mixed-integer Index (GH11320)
- Bug in `pivot_table` with `margins=True` when indexes are of `Categorical` dtype (GH10993)
- Bug in `DataFrame.plot` cannot use hex strings colors (GH10299)
- Regression in `DataFrame.drop_duplicates` from 0.16.2, causing incorrect results on integer values (GH11376)
- Bug in `pd.eval` where unary ops in a list error (GH11235)
- Bug in `squeeze()` with zero length arrays (GH11230, GH8999)
- Bug in `describe()` dropping column names for hierarchical indexes (GH11517)
- Bug in `DataFrame.pct_change()` not propagating `axis` keyword on `.fillna` method (GH11150)
- Bug in `.to_csv()` when a mix of integer and string column names are passed as the `columns` parameter (GH11637)
- Bug in indexing with a `range`, (GH11652)
- Bug in inference of numpy scalars and preserving dtype when setting columns (GH11638)
- Bug in `to_sql` using unicode column names giving UnicodeEncodeError with (GH11431).
- Fix regression in setting of `xticks` in `plot` (GH11529).
- Bug in `holiday.dates` where observance rules could not be applied to holiday and doc enhancement (GH11477, GH11533)
- Fix plotting issues when having plain `Axes` instances instead of `SubplotAxes` (GH11520, GH11556).
- Bug in `DataFrame.to_latex()` produces an extra rule when `header=False` (GH7124)
- Bug in `df.groupby(...).apply(func)` when a func returns a `Series` containing a new datetimelike column (GH11324)
- Bug in `pandas.json` when file to load is big (GH11344)
- Bugs in `to_excel` with duplicate columns (GH11007, GH10982, GH10970)
- Fixed a bug that prevented the construction of an empty series of dtype `datetime64[ns, tz]` (GH11245).

- Bug in `read_excel` with MultiIndex containing integers (GH11317)
- Bug in `to_excel` with openpyxl 2.2+ and merging (GH11408)
- Bug in `DataFrame.to_dict()` produces a `np.datetime64` object instead of `Timestamp` when only datetime is present in data (GH11327)
- Bug in `DataFrame.corr()` raises exception when computes Kendall correlation for DataFrames with boolean and not boolean columns (GH11560)
- Bug in the link-time error caused by C `inline` functions on FreeBSD 10+ (with `clang`) (GH10510)
- Bug in `DataFrame.to_csv` in passing through arguments for formatting `MultiIndexes`, including `date_format` (GH7791)
- Bug in `DataFrame.join()` with `how='right'` producing a `TypeError` (GH11519)
- Bug in `Series.quantile` with empty list results has `Index` with `object` dtype (GH11588)
- Bug in `pd.merge` results in empty `Int64Index` rather than `Index(dtype=object)` when the merge result is empty (GH11588)
- Bug in `Categorical.remove_unused_categories` when having `NaN` values (GH11599)
- Bug in `DataFrame.to_sparse()` loses column names for MultiIndexes (GH11600)
- Bug in `DataFrame.round()` with non-unique column index producing a Fatal Python error (GH11611)
- Bug in `DataFrame.round()` with `decimals` being a non-unique indexed Series producing extra columns (GH11618)

Contributors

A total of 63 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.12.2 Version 0.17.0 (October 9, 2015)

This is a major release from 0.16.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Warning: pandas >= 0.17.0 will no longer support compatibility with Python version 3.2 (GH9118)

Warning: The `pandas.io.data` package is deprecated and will be replaced by the pandas-datareader package. This will allow the data modules to be independently updated to your pandas installation. The API for `pandas-datareader v0.1.1` is exactly the same as in `pandas v0.17.0` (GH8961, GH10861).

After installing pandas-datareader, you can easily change your imports:

```
from pandas.io import data, wb
```

becomes

```
from pandas_datareader import data, wb
```

Highlights include:

- Release the Global Interpreter Lock (GIL) on some cython operations, see *here*
- Plotting methods are now available as attributes of the `.plot` accessor, see *here*
- The sorting API has been revamped to remove some long-time inconsistencies, see *here*
- Support for a `datetime64[ns]` with timezones as a first-class dtype, see *here*
- The default for `to_datetime` will now be to `raise` when presented with unparsable formats, previously this would return the original input. Also, date parse functions now return consistent results. See *here*
- The default for `dropna` in `HDFStore` has changed to `False`, to store by default all rows even if they are all `NaN`, see *here*
- Datetime accessor (`dt`) now supports `Series.dt.strftime` to generate formatted strings for datetime-likes, and `Series.dt.total_seconds` to generate each duration of the timedelta in seconds. See *here*

- `Period` and `PeriodIndex` can handle multiplied freq like `3D`, which corresponding to 3 days span. See *here*
- Development installed versions of pandas will now have `PEP440` compliant version strings (GH9518)
- Development support for benchmarking with the Air Speed Velocity library (GH8361)
- Support for reading SAS xport files, see *here*
- Documentation comparing SAS to *pandas*, see *here*
- Removal of the automatic TimeSeries broadcasting, deprecated since 0.8.0, see *here*
- Display format with plain text can optionally align with Unicode East Asian Width, see *here*
- Compatibility with Python 3.5 (GH11097)
- Compatibility with matplotlib 1.5.0 (GH11111)

Check the *API Changes* and *deprecations* before updating.

What's new in v0.17.0

- *New features*
  - *Datetime with TZ*
  - *Releasing the GIL*
  - *Plot submethods*
  - *Additional methods for `dt` accessor*
    - *Series.dt.strftime*
    - *Series.dt.total_seconds*
  - *Period frequency enhancement*
  - *Support for SAS XPORT files*
  - *Support for math functions in .eval()*
  - *Changes to Excel with `MultiIndex`*
  - *Google BigQuery enhancements*
  - *Display alignment with Unicode East Asian width*
  - *Other enhancements*
- *Backwards incompatible API changes*
  - *Changes to sorting API*
  - *Changes to to_datetime and to_timedelta*
    - *Error handling*
    - *Consistent parsing*
  - *Changes to Index comparisons*
  - *Changes to boolean comparisons vs. None*
  - *HDFStore dropna behavior*
  - *Changes to `display.precision` option*
  - *Changes to `Categorical.unique`*

- *Changes to `bool` passed as `header` in parsers*
- *Other API changes*
- *Deprecations*
- *Removal of prior version deprecations/changes*

- *Performance improvements*
- *Bug fixes*
- *Contributors*

New features

Datetime with TZ

We are adding an implementation that natively supports datetime with timezones. A `Series` or a `DataFrame` column previously *could* be assigned a datetime with timezones, and would work as an `object` dtype. This had performance issues with a large number rows. See the *docs* for more details. (GH8260, GH10763, GH11034).

The new implementation allows for having a single-timezone across all rows, with operations in a performant manner.

```
In [1]: df = pd.DataFrame(
   ...:     {
   ...:         "A": pd.date_range("20130101", periods=3),
   ...:         "B": pd.date_range("20130101", periods=3, tz="US/Eastern"),
   ...:         "C": pd.date_range("20130101", periods=3, tz="CET"),
   ...:     }
   ...: )
   ...:

In [2]: df
Out[2]:
           A                          B                          C
0 2013-01-01 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00+01:00
1 2013-01-02 2013-01-02 00:00:00-05:00 2013-01-02 00:00:00+01:00
2 2013-01-03 2013-01-03 00:00:00-05:00 2013-01-03 00:00:00+01:00

[3 rows x 3 columns]

In [3]: df.dtypes
Out[3]:
A                datetime64[ns]
B    datetime64[ns, US/Eastern]
C           datetime64[ns, CET]
Length: 3, dtype: object
```

```
In [4]: df.B
Out[4]:
0   2013-01-01 00:00:00-05:00
1   2013-01-02 00:00:00-05:00
2   2013-01-03 00:00:00-05:00
Name: B, Length: 3, dtype: datetime64[ns, US/Eastern]

In [5]: df.B.dt.tz_localize(None)
```

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```
Out[5]:
0   2013-01-01
1   2013-01-02
2   2013-01-03
Name: B, Length: 3, dtype: datetime64[ns]
```

This uses a new-dtype representation as well, that is very similar in look-and-feel to its numpy cousin `datetime64[ns]`

```
In [6]: df["B"].dtype
Out[6]: datetime64[ns, US/Eastern]

In [7]: type(df["B"].dtype)
Out[7]: pandas.core.dtypes.dtypes.DatetimeTZDtype
```

Note: There is a slightly different string repr for the underlying `DatetimeIndex` as a result of the dtype changes, but functionally these are the same.

Previous behavior:

```
In [1]: pd.date_range('20130101', periods=3, tz='US/Eastern')
Out[1]: DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
                       '2013-01-03 00:00:00-05:00'],
                      dtype='datetime64[ns]', freq='D', tz='US/Eastern')

In [2]: pd.date_range('20130101', periods=3, tz='US/Eastern').dtype
Out[2]: dtype('<M8[ns]')
```

New behavior:

```
In [8]: pd.date_range("20130101", periods=3, tz="US/Eastern")
Out[8]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
               '2013-01-03 00:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='D')

In [9]: pd.date_range("20130101", periods=3, tz="US/Eastern").dtype
Out[9]: datetime64[ns, US/Eastern]
```

Releasing the GIL

We are releasing the global-interpreter-lock (GIL) on some cython operations. This will allow other threads to run simultaneously during computation, potentially allowing performance improvements from multi-threading. Notably `groupby`, `nsmallest`, `value_counts` and some indexing operations benefit from this. (GH8882)

For example the groupby expression in the following code will have the GIL released during the factorization step, e.g. `df.groupby('key')` as well as the `.sum()` operation.

```
N = 1000000
ngroups = 10
df = DataFrame(
    {"key": np.random.randint(0, ngroups, size=N), "data": np.random.randn(N)}
```

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```
)
df.groupby("key")["data"].sum()
```

Releasing of the GIL could benefit an application that uses threads for user interactions (e.g. QT), or performing multi-threaded computations. A nice example of a library that can handle these types of computation-in-parallel is the dask library.

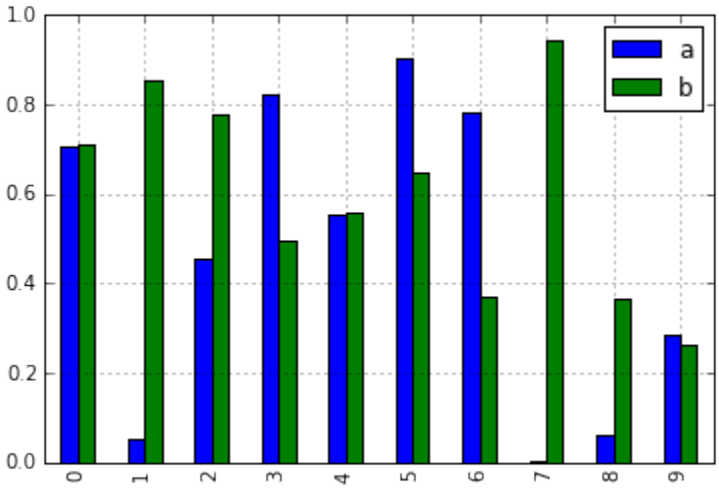
Plot submethods

The Series and DataFrame `.plot()` method allows for customizing *plot types* by supplying the `kind` keyword arguments. Unfortunately, many of these kinds of plots use different required and optional keyword arguments, which makes it difficult to discover what any given plot kind uses out of the dozens of possible arguments.

To alleviate this issue, we have added a new, optional plotting interface, which exposes each kind of plot as a method of the `.plot` attribute. Instead of writing `series.plot(kind=<kind>, ...)`, you can now also use `series.plot.<kind>(...)`:

```
In [10]: df = pd.DataFrame(np.random.rand(10, 2), columns=['a', 'b'])

In [11]: df.plot.bar()
```



As a result of this change, these methods are now all discoverable via tab-completion:

```
In [12]: df.plot.<TAB>  # noqa: E225, E999
df.plot.area     df.plot.barh     df.plot.density  df.plot.hist     df.plot.line
↪df.plot.scatter
df.plot.bar      df.plot.box      df.plot.hexbin   df.plot.kde      df.plot.pie
```

Each method signature only includes relevant arguments. Currently, these are limited to required arguments, but in the future these will include optional arguments, as well. For an overview, see the new *Plotting* API documentation.

Additional methods for `dt` accessor

Series.dt.strftime

We are now supporting a `Series.dt.strftime` method for datetime-likes to generate a formatted string (GH10110). Examples:

```
# DatetimeIndex
In [13]: s = pd.Series(pd.date_range("20130101", periods=4))

In [14]: s
Out[14]:
0   2013-01-01
1   2013-01-02
2   2013-01-03
3   2013-01-04
Length: 4, dtype: datetime64[ns]

In [15]: s.dt.strftime("%Y/%m/%d")
Out[15]:
0    2013/01/01
1    2013/01/02
2    2013/01/03
3    2013/01/04
Length: 4, dtype: object
```

```
# PeriodIndex
In [16]: s = pd.Series(pd.period_range("20130101", periods=4))

In [17]: s
Out[17]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
Length: 4, dtype: period[D]

In [18]: s.dt.strftime("%Y/%m/%d")
Out[18]:
0    2013/01/01
1    2013/01/02
2    2013/01/03
3    2013/01/04
Length: 4, dtype: object
```

The string format is as the python standard library and details can be found here

Series.dt.total_seconds

`pd.Series` of type `timedelta64` has new method `.dt.total_seconds()` returning the duration of the timedelta in seconds (GH10817)

```
# TimedeltaIndex
In [19]: s = pd.Series(pd.timedelta_range("1 minutes", periods=4))

In [20]: s
Out[20]:
0   0 days 00:01:00
1   1 days 00:01:00
2   2 days 00:01:00
3   3 days 00:01:00
Length: 4, dtype: timedelta64[ns]

In [21]: s.dt.total_seconds()
Out[21]:
0        60.0
1     86460.0
2    172860.0
3    259260.0
Length: 4, dtype: float64
```

Period frequency enhancement

`Period`, `PeriodIndex` and `period_range` can now accept multiplied freq. Also, `Period.freq` and `PeriodIndex.freq` are now stored as a `DateOffset` instance like `DatetimeIndex`, and not as `str` (GH7811)

A multiplied freq represents a span of corresponding length. The example below creates a period of 3 days. Addition and subtraction will shift the period by its span.

```
In [22]: p = pd.Period("2015-08-01", freq="3D")

In [23]: p
Out[23]: Period('2015-08-01', '3D')

In [24]: p + 1
Out[24]: Period('2015-08-04', '3D')

In [25]: p - 2
Out[25]: Period('2015-07-26', '3D')

In [26]: p.to_timestamp()
Out[26]: Timestamp('2015-08-01 00:00:00')

In [27]: p.to_timestamp(how="E")
Out[27]: Timestamp('2015-08-03 23:59:59.999999999')
```

You can use the multiplied freq in `PeriodIndex` and `period_range`.

```
In [28]: idx = pd.period_range("2015-08-01", periods=4, freq="2D")

In [29]: idx
Out[29]: PeriodIndex(['2015-08-01', '2015-08-03', '2015-08-05', '2015-08-07'], dtype=
↪'period[2D]', freq='2D')
```

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```
In [30]: idx + 1
Out[30]: PeriodIndex(['2015-08-03', '2015-08-05', '2015-08-07', '2015-08-09'], dtype=
↪'period[2D]', freq='2D')
```

Support for SAS XPORT files

`read_sas()` provides support for reading *SAS XPORT* format files. (GH4052).

```
df = pd.read_sas("sas_xport.xpt")
```

It is also possible to obtain an iterator and read an XPORT file incrementally.

```
for df in pd.read_sas("sas_xport.xpt", chunksize=10000):
    do_something(df)
```

See the *docs* for more details.

Support for math functions in .eval()

`eval()` now supports calling math functions (GH4893)

```
df = pd.DataFrame({"a": np.random.randn(10)})
df.eval("b = sin(a)")
```

The support math functions are `sin`, `cos`, `exp`, `log`, `expm1`, `log1p`, `sqrt`, `sinh`, `cosh`, `tanh`, `arcsin`, `arccos`, `arctan`, `arccosh`, `arcsinh`, `arctanh`, `abs` and `arctan2`.

These functions map to the intrinsics for the `NumExpr` engine. For the Python engine, they are mapped to `NumPy` calls.

Changes to Excel with `MultiIndex`

In version 0.16.2 a `DataFrame` with `MultiIndex` columns could not be written to Excel via `to_excel`. That functionality has been added (GH10564), along with updating `read_excel` so that the data can be read back with, no loss of information, by specifying which columns/rows make up the `MultiIndex` in the `header` and `index_col` parameters (GH4679)

See the *documentation* for more details.

```
In [31]: df = pd.DataFrame(
   ....:     [[1, 2, 3, 4], [5, 6, 7, 8]],
   ....:     columns=pd.MultiIndex.from_product(
   ....:         [["foo", "bar"], ["a", "b"]], names=["col1", "col2"]
   ....:     ),
   ....:     index=pd.MultiIndex.from_product([["j"], ["l", "k"]], names=["i1", "i2
↪"]),
   ....: )
   ....:

In [32]: df
Out[32]:
```

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```
col1  foo    bar
col2    a  b   a  b
i1 i2
j  l    1  2   3  4
   k    5  6   7  8

[2 rows x 4 columns]

In [33]: df.to_excel("test.xlsx")

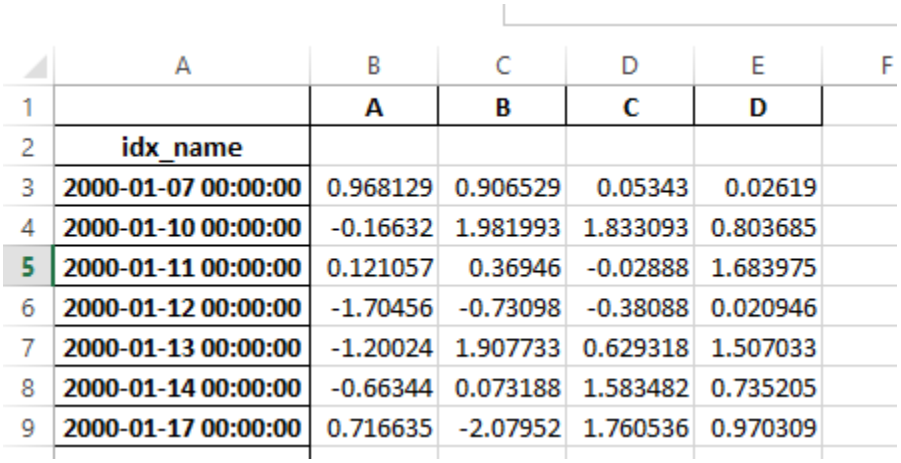
In [34]: df = pd.read_excel("test.xlsx", header=[0, 1], index_col=[0, 1])

In [35]: df
Out[35]:
col1  foo    bar
col2    a  b   a  b
i1 i2
j  l    1  2   3  4
   k    5  6   7  8

[2 rows x 4 columns]
```

Previously, it was necessary to specify the `has_index_names` argument in `read_excel`, if the serialized data had index names. For version 0.17.0 the output format of `to_excel` has been changed to make this keyword unnecessary - the change is shown below.

Old



	A	B	C	D	E	F
1		A	B	C	D	
2	idx_name					
3	2000-01-07 00:00:00	0.968129	0.906529	0.05343	0.02619	
4	2000-01-10 00:00:00	-0.16632	1.981993	1.833093	0.803685	
5	2000-01-11 00:00:00	0.121057	0.36946	-0.02888	1.683975	
6	2000-01-12 00:00:00	-1.70456	-0.73098	-0.38088	0.020946	
7	2000-01-13 00:00:00	-1.20024	1.907733	0.629318	1.507033	
8	2000-01-14 00:00:00	-0.66344	0.073188	1.583482	0.735205	
9	2000-01-17 00:00:00	0.716635	-2.07952	1.760536	0.970309	

New

	A	B	C	D	E
1	idx_name	A	B	C	D
2	2000-01-07 00:00:00	0.968129	0.906529	0.05343	0.02619
3	2000-01-10 00:00:00	-0.16632	1.981993	1.833093	0.803685
4	2000-01-11 00:00:00	0.121057	0.36946	-0.02888	1.683975
5	2000-01-12 00:00:00	-1.70456	-0.73098	-0.38088	0.020946
6	2000-01-13 00:00:00	-1.20024	1.907733	0.629318	1.507033
7	2000-01-14 00:00:00	-0.66344	0.073188	1.583482	0.735205
8	2000-01-17 00:00:00	0.716635	-2.07952	1.760536	0.970309
9	2000-01-18 00:00:00	0.737628	2.32367	2.706276	0.691843

Warning: Excel files saved in version 0.16.2 or prior that had index names will still able to be read in, but the `has_index_names` argument must specified to `True`.

Google BigQuery enhancements

- Added ability to automatically create a table/dataset using the `pandas.io.gbq.to_gbq()` function if the destination table/dataset does not exist. (GH8325, GH11121).
- Added ability to replace an existing table and schema when calling the `pandas.io.gbq.to_gbq()` function via the `if_exists` argument. See the docs for more details (GH8325).
- `InvalidColumnOrder` and `InvalidPageToken` in the gbq module will raise `ValueError` instead of `IOError`.
- The `generate_bq_schema()` function is now deprecated and will be removed in a future version (GH11121)
- The gbq module will now support Python 3 (GH11094).

Display alignment with Unicode East Asian width

Warning: Enabling this option will affect the performance for printing of `DataFrame` and `Series` (about 2 times slower). Use only when it is actually required.

Some East Asian countries use Unicode characters its width is corresponding to 2 alphabets. If a `DataFrame` or `Series` contains these characters, the default output cannot be aligned properly. The following options are added to enable precise handling for these characters.

- `display.unicode.east_asian_width`: Whether to use the Unicode East Asian Width to calculate the display text width. (GH2612)
- `display.unicode.ambiguous_as_wide`: Whether to handle Unicode characters belong to Ambiguous as Wide. (GH11102)

```
In [36]: df = pd.DataFrame({u"": ["UK", u""], u"": ["Alice", u""]})

In [37]: df;
```

```
>>> df = pd.DataFrame({u'国籍': ['UK', u'日本'], u'名前': ['Alice', u'しのぶ']})
>>> df
     名前  国籍
0  Alice  UK
1   しのぶ  日本
```

```
In [38]: pd.set_option("display.unicode.east_asian_width", True)

In [39]: df;
```

```
>>> pd.set_option('display.unicode.east_asian_width', True)
>>> df
     名前  国籍
0   Alice   UK
1  しのぶ  日本
```

For further details, see *here*

Other enhancements

- Support for `openpyxl` >= 2.2. The API for style support is now stable (GH10125)
- `merge` now accepts the argument `indicator` which adds a Categorical-type column (by default called `_merge`) to the output object that takes on the values (GH8790)

Observation Origin	`_merge` value
Merge key only in `'left'` frame	`left_only`
Merge key only in `'right'` frame	`right_only`
Merge key in both frames	`both`

```
In [40]: df1 = pd.DataFrame({"col1": [0, 1], "col_left": ["a", "b"]})

In [41]: df2 = pd.DataFrame({"col1": [1, 2, 2], "col_right": [2, 2, 2]})

In [42]: pd.merge(df1, df2, on="col1", how="outer", indicator=True)
Out[42]:
   col1 col_left  col_right      _merge
0     0        a        NaN   left_only
1     1        b        2.0        both
2     2      NaN        2.0  right_only
3     2      NaN        2.0  right_only

[4 rows x 4 columns]
```

For more, see the *updated docs*

- `pd.to_numeric` is a new function to coerce strings to numbers (possibly with coercion) (GH11133)
- `pd.merge` will now allow duplicate column names if they are not merged upon (GH10639).
- `pd.pivot` will now allow passing index as `None` (GH3962).
- `pd.concat` will now use existing Series names if provided (GH10698).

```
In [43]: foo = pd.Series([1, 2], name="foo")

In [44]: bar = pd.Series([1, 2])
```

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```
In [45]: baz = pd.Series([4, 5])
```

Previous behavior:

```
In [1]: pd.concat([foo, bar, baz], 1)
Out[1]:
   0  1  2
0  1  1  4
1  2  2  5
```

New behavior:

```
In [46]: pd.concat([foo, bar, baz], 1)
Out[46]:
   foo  0  1
0    1  1  4
1    2  2  5

[2 rows x 3 columns]
```

- `DataFrame` has gained the `nlargest` and `nsmallest` methods (GH10393)
- Add a `limit_direction` keyword argument that works with `limit` to enable `interpolate` to fill `NaN` values forward, backward, or both (GH9218, GH10420, GH11115)

```
In [47]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, np.nan, 13])

In [48]: ser.interpolate(limit=1, limit_direction="both")
Out[48]:
0     NaN
1     5.0
2     5.0
3     7.0
4     NaN
5    11.0
6    13.0
Length: 7, dtype: float64
```

- Added a `DataFrame.round` method to round the values to a variable number of decimal places (GH10568).

```
In [49]: df = pd.DataFrame(
   ....:     np.random.random([3, 3]),
   ....:     columns=["A", "B", "C"],
   ....:     index=["first", "second", "third"],
   ....: )
   ....:

In [50]: df
Out[50]:
               A         B         C
first   0.126970  0.966718  0.260476
second  0.897237  0.376750  0.336222
third   0.451376  0.840255  0.123102

[3 rows x 3 columns]
```

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```
In [51]: df.round(2)
Out[51]:
            A     B     C
first    0.13  0.97  0.26
second   0.90  0.38  0.34
third    0.45  0.84  0.12

[3 rows x 3 columns]

In [52]: df.round({"A": 0, "C": 2})
Out[52]:
           A         B     C
first    0.0  0.966718  0.26
second   1.0  0.376750  0.34
third    0.0  0.840255  0.12

[3 rows x 3 columns]
```

- `drop_duplicates` and `duplicated` now accept a `keep` keyword to target first, last, and all duplicates. The `take_last` keyword is deprecated, see *here* (GH6511, GH8505)

```
In [53]: s = pd.Series(["A", "B", "C", "A", "B", "D"])

In [54]: s.drop_duplicates()
Out[54]:
0    A
1    B
2    C
5    D
Length: 4, dtype: object

In [55]: s.drop_duplicates(keep="last")
Out[55]:
2    C
3    A
4    B
5    D
Length: 4, dtype: object

In [56]: s.drop_duplicates(keep=False)
Out[56]:
2    C
5    D
Length: 2, dtype: object
```

- Reindex now has a `tolerance` argument that allows for finer control of *Limits on filling while reindexing* (GH10411):

```
In [57]: df = pd.DataFrame({"x": range(5), "t": pd.date_range("2000-01-01",␣
↪periods=5)})

In [58]: df.reindex([0.1, 1.9, 3.5], method="nearest", tolerance=0.2)
Out[58]:
       x          t
0.1  0.0 2000-01-01
1.9  2.0 2000-01-03
```

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```
3.5  NaN        NaT

[3 rows x 2 columns]
```

When used on a `DatetimeIndex`, `TimedeltaIndex` or `PeriodIndex`, `tolerance` will coerced into a `Timedelta` if possible. This allows you to specify tolerance with a string:

```
In [59]: df = df.set_index("t")

In [60]: df.reindex(pd.to_datetime(["1999-12-31"]), method="nearest", tolerance=
↪"1 day")
Out[60]:
              x
1999-12-31  0

[1 rows x 1 columns]
```

`tolerance` is also exposed by the lower level `Index.get_indexer` and `Index.get_loc` methods.

- Added functionality to use the `base` argument when resampling a `TimeDeltaIndex` (GH10530)
- `DatetimeIndex` can be instantiated using strings contains `NaT` (GH7599)
- `to_datetime` can now accept the `yearfirst` keyword (GH7599)
- `pandas.tseries.offsets` larger than the `Day` offset can now be used with a `Series` for addition/subtraction (GH10699). See the *docs* for more details.
- `pd.Timedelta.total_seconds()` now returns Timedelta duration to ns precision (previously microsecond precision) (GH10939)
- `PeriodIndex` now supports arithmetic with `np.ndarray` (GH10638)
- Support pickling of `Period` objects (GH10439)
- `.as_blocks` will now take a `copy` optional argument to return a copy of the data, default is to copy (no change in behavior from prior versions), (GH9607)
- `regex` argument to `DataFrame.filter` now handles numeric column names instead of raising `ValueError` (GH10384).
- Enable reading gzip compressed files via URL, either by explicitly setting the compression parameter or by inferring from the presence of the HTTP Content-Encoding header in the response (GH8685)
- Enable writing Excel files in *memory* using StringIO/BytesIO (GH7074)
- Enable serialization of lists and dicts to strings in `ExcelWriter` (GH8188)
- SQL io functions now accept a SQLAlchemy connectable. (GH7877)
- `pd.read_sql` and `to_sql` can accept database URI as `con` parameter (GH10214)
- `read_sql_table` will now allow reading from views (GH10750).
- Enable writing complex values to `HDFStores` when using the `table` format (GH10447)
- Enable `pd.read_hdf` to be used without specifying a key when the HDF file contains a single dataset (GH10443)
- `pd.read_stata` will now read Stata 118 type files. (GH9882)
- `msgpack` submodule has been updated to 0.4.6 with backward compatibility (GH10581)
- `DataFrame.to_dict` now accepts `orient='index'` keyword argument (GH10844).

- `DataFrame.apply` will return a Series of dicts if the passed function returns a dict and `reduce=True` (GH8735).
- Allow passing `kwargs` to the interpolation methods (GH10378).
- Improved error message when concatenating an empty iterable of `Dataframe` objects (GH9157)
- `pd.read_csv` can now read bz2-compressed files incrementally, and the C parser can read bz2-compressed files from AWS S3 (GH11070, GH11072).
- In `pd.read_csv`, recognize `s3n://` and `s3a://` URLs as designating S3 file storage (GH11070, GH11071).
- Read CSV files from AWS S3 incrementally, instead of first downloading the entire file. (Full file download still required for compressed files in Python 2.) (GH11070, GH11073)
- `pd.read_csv` is now able to infer compression type for files read from AWS S3 storage (GH11070, GH11074).

Backwards incompatible API changes

Changes to sorting API

The sorting API has had some longtime inconsistencies. (GH9816, GH8239).

Here is a summary of the API **PRIOR** to 0.17.0:

- `Series.sort` is **INPLACE** while `DataFrame.sort` returns a new object.
- `Series.order` returns a new object
- It was possible to use `Series/DataFrame.sort_index` to sort by **values** by passing the `by` keyword.
- `Series/DataFrame.sortlevel` worked only on a `MultiIndex` for sorting by index.

To address these issues, we have revamped the API:

- We have introduced a new method, *`DataFrame.sort_values()`*, which is the merger of `DataFrame.sort()`, `Series.sort()`, and `Series.order()`, to handle sorting of **values**.
- The existing methods `Series.sort()`, `Series.order()`, and `DataFrame.sort()` have been deprecated and will be removed in a future version.
- The `by` argument of `DataFrame.sort_index()` has been deprecated and will be removed in a future version.
- The existing method `.sort_index()` will gain the `level` keyword to enable level sorting.

We now have two distinct and non-overlapping methods of sorting. A `*` marks items that will show a `FutureWarning`.

To sort by the **values**:

Previous	Replacement
* `Series.order()`	`Series.sort_values()`
* `Series.sort()`	`Series.sort_values(inplace=True)`
* `DataFrame.sort(columns=...)`	`DataFrame.sort_values(by=...)`

To sort by the **index**:

Previous	Replacement
`Series.sort_index()`	`Series.sort_index()`
`Series.sortlevel(level=...)`	`Series.sort_index(level=...)`
`DataFrame.sort_index()`	`DataFrame.sort_index()`
`DataFrame.sortlevel(level=...)`	`DataFrame.sort_index(level=...)`
`*DataFrame.sort()`	`DataFrame.sort_index()`

We have also deprecated and changed similar methods in two Series-like classes, `Index` and `Categorical`.

Previous	Replacement
`*Index.order()`	`Index.sort_values()`
`*Categorical.order()`	`Categorical.sort_values()`

Changes to to_datetime and to_timedelta

Error handling

The default for `pd.to_datetime` error handling has changed to `errors='raise'`. In prior versions it was `errors='ignore'`. Furthermore, the `coerce` argument has been deprecated in favor of `errors='coerce'`. This means that invalid parsing will raise rather that return the original input as in previous versions. (GH10636)

Previous behavior:

```
In [2]: pd.to_datetime(['2009-07-31', 'asd'])
Out[2]: array(['2009-07-31', 'asd'], dtype=object)
```

New behavior:

```
In [3]: pd.to_datetime(['2009-07-31', 'asd'])
ValueError: Unknown string format
```

Of course you can coerce this as well.

```
In [61]: pd.to_datetime(["2009-07-31", "asd"], errors="coerce")
Out[61]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)
```

To keep the previous behavior, you can use `errors='ignore'`:

```
In [62]: pd.to_datetime(["2009-07-31", "asd"], errors="ignore")
Out[62]: Index(['2009-07-31', 'asd'], dtype='object')
```

Furthermore, `pd.to_timedelta` has gained a similar API, of `errors='raise'|'ignore'|'coerce'`, and the `coerce` keyword has been deprecated in favor of `errors='coerce'`.

Consistent parsing

The string parsing of `to_datetime`, `Timestamp` and `DatetimeIndex` has been made consistent. (GH7599)

Prior to v0.17.0, `Timestamp` and `to_datetime` may parse year-only datetime-string incorrectly using today's date, otherwise `DatetimeIndex` uses the beginning of the year. `Timestamp` and `to_datetime` may raise `ValueError` in some types of datetime-string which `DatetimeIndex` can parse, such as a quarterly string.

Previous behavior:

```
In [1]: pd.Timestamp('2012Q2')
Traceback
   ...
ValueError: Unable to parse 2012Q2

# Results in today's date.
In [2]: pd.Timestamp('2014')
Out [2]: 2014-08-12 00:00:00
```

v0.17.0 can parse them as below. It works on `DatetimeIndex` also.

New behavior:

```
In [63]: pd.Timestamp("2012Q2")
Out[63]: Timestamp('2012-04-01 00:00:00')

In [64]: pd.Timestamp("2014")
Out[64]: Timestamp('2014-01-01 00:00:00')

In [65]: pd.DatetimeIndex(["2012Q2", "2014"])
Out[65]: DatetimeIndex(['2012-04-01', '2014-01-01'], dtype='datetime64[ns]',␣
↪freq=None)
```

Note: If you want to perform calculations based on today's date, use `Timestamp.now()` and `pandas.tseries.offsets`.

```
In [66]: import pandas.tseries.offsets as offsets

In [67]: pd.Timestamp.now()
Out[67]: Timestamp('2021-02-09 11:34:45.455167')

In [68]: pd.Timestamp.now() + offsets.DateOffset(years=1)
Out[68]: Timestamp('2022-02-09 11:34:45.455798')
```

Changes to Index comparisons

Operator equal on `Index` should behavior similarly to `Series` (GH9947, GH10637)

Starting in v0.17.0, comparing `Index` objects of different lengths will raise a `ValueError`. This is to be consistent with the behavior of `Series`.

Previous behavior:

```
In [2]: pd.Index([1, 2, 3]) == pd.Index([1, 4, 5])
Out[2]: array([ True, False, False], dtype=bool)
```

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```
In [3]: pd.Index([1, 2, 3]) == pd.Index([2])
Out[3]: array([False,  True, False], dtype=bool)

In [4]: pd.Index([1, 2, 3]) == pd.Index([1, 2])
Out[4]: False
```

New behavior:

```
In [8]: pd.Index([1, 2, 3]) == pd.Index([1, 4, 5])
Out[8]: array([ True, False, False], dtype=bool)

In [9]: pd.Index([1, 2, 3]) == pd.Index([2])
ValueError: Lengths must match to compare

In [10]: pd.Index([1, 2, 3]) == pd.Index([1, 2])
ValueError: Lengths must match to compare
```

Note that this is different from the `numpy` behavior where a comparison can be broadcast:

```
In [69]: np.array([1, 2, 3]) == np.array([1])
Out[69]: array([ True, False, False])
```

or it can return False if broadcasting can not be done:

```
In [70]: np.array([1, 2, 3]) == np.array([1, 2])
Out[70]: False
```

Changes to boolean comparisons vs. None

Boolean comparisons of a `Series` vs `None` will now be equivalent to comparing with `np.nan`, rather than raise `TypeError`. (GH1079).

```
In [71]: s = pd.Series(range(3))

In [72]: s.iloc[1] = None

In [73]: s
Out[73]:
0    0.0
1    NaN
2    2.0
Length: 3, dtype: float64
```

Previous behavior:

```
In [5]: s == None
TypeError: Could not compare <type 'NoneType'> type with Series
```

New behavior:

```
In [74]: s == None
Out[74]:
0    False
```

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```
1    False
2    False
Length: 3, dtype: bool
```

Usually you simply want to know which values are null.

```
In [75]: s.isnull()
Out[75]:
0    False
1     True
2    False
Length: 3, dtype: bool
```

Warning: You generally will want to use `isnull/notnull` for these types of comparisons, as `isnull/notnull` tells you which elements are null. One has to be mindful that `nan`'s don't compare equal, but `None`'s do. Note that pandas/numpy uses the fact that `np.nan != np.nan`, and treats `None` like `np.nan`.

```
In [76]: None == None
Out[76]: True

In [77]: np.nan == np.nan
Out[77]: False
```

HDFStore dropna behavior

The default behavior for HDFStore write functions with `format='table'` is now to keep rows that are all missing. Previously, the behavior was to drop rows that were all missing save the index. The previous behavior can be replicated using the `dropna=True` option. (GH9382)

Previous behavior:

```
In [78]: df_with_missing = pd.DataFrame(
   ....:     {"col1": [0, np.nan, 2], "col2": [1, np.nan, np.nan]}
   ....: )
   ....:

In [79]: df_with_missing
Out[79]:
   col1  col2
0   0.0   1.0
1   NaN   NaN
2   2.0   NaN

[3 rows x 2 columns]
```

```
In [27]:
df_with_missing.to_hdf('file.h5',
                       'df_with_missing',
                       format='table',
                       mode='w')

In [28]: pd.read_hdf('file.h5', 'df_with_missing')
```

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```
Out [28]:
      col1  col2
  0      0     1
  2      2   NaN
```

New behavior:

```
In [80]: df_with_missing.to_hdf("file.h5", "df_with_missing", format="table", mode="w
↪")

In [81]: pd.read_hdf("file.h5", "df_with_missing")
Out[81]:
   col1  col2
0   0.0   1.0
1   NaN   NaN
2   2.0   NaN

[3 rows x 2 columns]
```

See the *docs* for more details.

Changes to `display.precision` option

The `display.precision` option has been clarified to refer to decimal places (GH10451).

Earlier versions of pandas would format floating point numbers to have one less decimal place than the value in `display.precision`.

```
In [1]: pd.set_option('display.precision', 2)

In [2]: pd.DataFrame({'x': [123.456789]})
Out[2]:
       x
0  123.5
```

If interpreting precision as "significant figures" this did work for scientific notation but that same interpretation did not work for values with standard formatting. It was also out of step with how numpy handles formatting.

Going forward the value of `display.precision` will directly control the number of places after the decimal, for regular formatting as well as scientific notation, similar to how numpy's `precision` print option works.

```
In [82]: pd.set_option("display.precision", 2)

In [83]: pd.DataFrame({"x": [123.456789]})
Out[83]:
        x
0  123.46

[1 rows x 1 columns]
```

To preserve output behavior with prior versions the default value of `display.precision` has been reduced to `6` from `7`.

Changes to `Categorical.unique`

`Categorical.unique` now returns new `Categoricals` with `categories` and `codes` that are unique, rather than returning `np.array` (GH10508)

- unordered category: values and categories are sorted by appearance order.
- ordered category: values are sorted by appearance order, categories keep existing order.

```
In [84]: cat = pd.Categorical(["C", "A", "B", "C"], categories=["A", "B", "C"],␣
↪ordered=True)

In [85]: cat
Out[85]:
['C', 'A', 'B', 'C']
Categories (3, object): ['A' < 'B' < 'C']

In [86]: cat.unique()
Out[86]:
['C', 'A', 'B']
Categories (3, object): ['A' < 'B' < 'C']

In [87]: cat = pd.Categorical(["C", "A", "B", "C"], categories=["A", "B", "C"])

In [88]: cat
Out[88]:
['C', 'A', 'B', 'C']
Categories (3, object): ['A', 'B', 'C']

In [89]: cat.unique()
Out[89]:
['C', 'A', 'B']
Categories (3, object): ['C', 'A', 'B']
```

Changes to `bool` passed as `header` in parsers

In earlier versions of pandas, if a bool was passed the `header` argument of `read_csv`, `read_excel`, or `read_html` it was implicitly converted to an integer, resulting in `header=0` for `False` and `header=1` for `True` (GH6113)

A `bool` input to `header` will now raise a `TypeError`

```
In [29]: df = pd.read_csv('data.csv', header=False)
TypeError: Passing a bool to header is invalid. Use header=None for no header or
header=int or list-like of ints to specify the row(s) making up the column names
```

Other API changes

- Line and kde plot with `subplots=True` now uses default colors, not all black. Specify `color='k'` to draw all lines in black (GH9894)
- Calling the `.value_counts()` method on a Series with a `categorical` dtype now returns a Series with a `CategoricalIndex` (GH10704)
- The metadata properties of subclasses of pandas objects will now be serialized (GH10553).
- `groupby` using `Categorical` follows the same rule as `Categorical.unique` described above (GH10508)
- When constructing `DataFrame` with an array of `complex64` dtype previously meant the corresponding column was automatically promoted to the `complex128` dtype. pandas will now preserve the itemsize of the input for complex data (GH10952)
- some numeric reduction operators would return `ValueError`, rather than `TypeError` on object types that includes strings and numbers (GH11131)
- Passing currently unsupported `chunksize` argument to `read_excel` or `ExcelFile.parse` will now raise `NotImplementedError` (GH8011)
- Allow an `ExcelFile` object to be passed into `read_excel` (GH11198)
- `DatetimeIndex.union` does not infer `freq` if `self` and the input have `None` as `freq` (GH11086)
- `NaT`'s methods now either raise `ValueError`, or return `np.nan` or `NaT` (GH9513)

Behavior	Methods
return `np.nan`	`weekday`, `isoweekday`
return `NaT`	`date`, `now`, `replace`, `to_datetime`, `today`
return `np.datetime64('NaT')`	`to_datetime64` (unchanged)
raise `ValueError`	All other public methods (names not beginning with underscores)

Deprecations

- For `Series` the following indexing functions are deprecated (GH10177).

Deprecated Function	Replacement
`.irow(i)`	`.iloc[i]` or `.iat[i]`
`.iget(i)`	`.iloc[i]` or `.iat[i]`
`.iget_value(i)`	`.iloc[i]` or `.iat[i]`

- For `DataFrame` the following indexing functions are deprecated (GH10177).

Deprecated Function	Replacement
`.irow(i)`	`.iloc[i]`
`.iget_value(i, j)`	`.iloc[i, j]` or `.iat[i, j]`
`.icol(j)`	`.iloc[:, j]`

Note: These indexing function have been deprecated in the documentation since 0.11.0.

- `Categorical.name` was deprecated to make `Categorical` more `numpy.ndarray` like. Use `Series(cat, name="whatever")` instead (GH10482).
- Setting missing values (NaN) in a `Categorical`'s `categories` will issue a warning (GH10748). You can still have missing values in the `values`.
- `drop_duplicates` and `duplicated`'s `take_last` keyword was deprecated in favor of `keep`. (GH6511, GH8505)
- `Series.nsmallest` and `nlargest`'s `take_last` keyword was deprecated in favor of `keep`. (GH10792)
- `DataFrame.combineAdd` and `DataFrame.combineMult` are deprecated. They can easily be replaced by using the `add` and `mul` methods: `DataFrame.add(other, fill_value=0)` and `DataFrame.mul(other, fill_value=1.)` (GH10735).
- `TimeSeries` deprecated in favor of `Series` (note that this has been an alias since 0.13.0), (GH10890)
- `SparsePanel` deprecated and will be removed in a future version (GH11157).
- `Series.is_time_series` deprecated in favor of `Series.index.is_all_dates` (GH11135)
- Legacy offsets (like `'A@JAN'`) are deprecated (note that this has been alias since 0.8.0) (GH10878)
- `WidePanel` deprecated in favor of `Panel`, `LongPanel` in favor of `DataFrame` (note these have been aliases since < 0.11.0), (GH10892)
- `DataFrame.convert_objects` has been deprecated in favor of type-specific functions `pd.to_datetime`, `pd.to_timestamp` and `pd.to_numeric` (new in 0.17.0) (GH11133).

Removal of prior version deprecations/changes

- Removal of `na_last` parameters from `Series.order()` and `Series.sort()`, in favor of `na_position`. (GH5231)
- Remove of `percentile_width` from `.describe()`, in favor of `percentiles`. (GH7088)
- Removal of `colSpace` parameter from `DataFrame.to_string()`, in favor of `col_space`, circa 0.8.0 version.
- Removal of automatic time-series broadcasting (GH2304)

```
In [90]: np.random.seed(1234)

In [91]: df = pd.DataFrame(
   ....:     np.random.randn(5, 2),
   ....:     columns=list("AB"),
   ....:     index=pd.date_range("2013-01-01", periods=5),
   ....: )
   ....:

In [92]: df
Out[92]:
                   A         B
2013-01-01  0.471435 -1.190976
2013-01-02  1.432707 -0.312652
2013-01-03 -0.720589  0.887163
2013-01-04  0.859588 -0.636524
2013-01-05  0.015696 -2.242685

[5 rows x 2 columns]
```

Previously

```
In [3]: df + df.A
FutureWarning: TimeSeries broadcasting along DataFrame index by default is␣
↪deprecated.
Please use DataFrame.<op> to explicitly broadcast arithmetic operations along the␣
↪index

Out[3]:
                   A         B
2013-01-01  0.942870 -0.719541
2013-01-02  2.865414  1.120055
2013-01-03 -1.441177  0.166574
2013-01-04  1.719177  0.223065
2013-01-05  0.031393 -2.226989
```

Current

```
In [93]: df.add(df.A, axis="index")
Out[93]:
                   A         B
2013-01-01  0.942870 -0.719541
2013-01-02  2.865414  1.120055
2013-01-03 -1.441177  0.166574
2013-01-04  1.719177  0.223065
2013-01-05  0.031393 -2.226989

[5 rows x 2 columns]
```

- Remove `table` keyword in `HDFStore.put/append`, in favor of using `format=` (GH4645)
- Remove `kind` in `read_excel/ExcelFile` as its unused (GH4712)
- Remove `infer_type` keyword from `pd.read_html` as its unused (GH4770, GH7032)
- Remove `offset` and `timeRule` keywords from `Series.tshift/shift`, in favor of `freq` (GH4853, GH4864)
- Remove `pd.load/pd.save` aliases in favor of `pd.to_pickle/pd.read_pickle` (GH3787)

Performance improvements

- Development support for benchmarking with the Air Speed Velocity library (GH8361)
- Added vbench benchmarks for alternative ExcelWriter engines and reading Excel files (GH7171)
- Performance improvements in `Categorical.value_counts` (GH10804)
- Performance improvements in `SeriesGroupBy.nunique` and `SeriesGroupBy.value_counts` and `SeriesGroupby.transform` (GH10820, GH11077)
- Performance improvements in `DataFrame.drop_duplicates` with integer dtypes (GH10917)
- Performance improvements in `DataFrame.duplicated` with wide frames. (GH10161, GH11180)
- 4x improvement in `timedelta` string parsing (GH6755, GH10426)
- 8x improvement in `timedelta64` and `datetime64` ops (GH6755)
- Significantly improved performance of indexing `MultiIndex` with slicers (GH10287)
- 8x improvement in `iloc` using list-like input (GH10791)

- Improved performance of `Series.isin` for datetimelike/integer Series (GH10287)
- 20x improvement in `concat` of Categoricals when categories are identical (GH10587)
- Improved performance of `to_datetime` when specified format string is ISO8601 (GH10178)
- 2x improvement of `Series.value_counts` for float dtype (GH10821)
- Enable `infer_datetime_format` in `to_datetime` when date components do not have 0 padding (GH11142)
- Regression from 0.16.1 in constructing `DataFrame` from nested dictionary (GH11084)
- Performance improvements in addition/subtraction operations for `DateOffset` with `Series` or `DatetimeIndex` (GH10744, GH11205)

Bug fixes

- Bug in incorrect computation of `.mean()` on `timedelta64[ns]` because of overflow (GH9442)
- Bug in `.isin` on older numpies (GH11232)
- Bug in `DataFrame.to_html(index=False)` renders unnecessary `name` row (GH10344)
- Bug in `DataFrame.to_latex()` the `column_format` argument could not be passed (GH9402)
- Bug in `DatetimeIndex` when localizing with `NaT` (GH10477)
- Bug in `Series.dt` ops in preserving meta-data (GH10477)
- Bug in preserving `NaT` when passed in an otherwise invalid `to_datetime` construction (GH10477)
- Bug in `DataFrame.apply` when function returns categorical series. (GH9573)
- Bug in `to_datetime` with invalid dates and formats supplied (GH10154)
- Bug in `Index.drop_duplicates` dropping name(s) (GH10115)
- Bug in `Series.quantile` dropping name (GH10881)
- Bug in `pd.Series` when setting a value on an empty `Series` whose index has a frequency. (GH10193)
- Bug in `pd.Series.interpolate` with invalid `order` keyword values. (GH10633)
- Bug in `DataFrame.plot` raises `ValueError` when color name is specified by multiple characters (GH10387)
- Bug in `Index` construction with a mixed list of tuples (GH10697)
- Bug in `DataFrame.reset_index` when index contains `NaT`. (GH10388)
- Bug in `ExcelReader` when worksheet is empty (GH6403)
- Bug in `BinGrouper.group_info` where returned values are not compatible with base class (GH10914)
- Bug in clearing the cache on `DataFrame.pop` and a subsequent inplace op (GH10912)
- Bug in indexing with a mixed-integer `Index` causing an `ImportError` (GH10610)
- Bug in `Series.count` when index has nulls (GH10946)
- Bug in pickling of a non-regular freq `DatetimeIndex` (GH11002)
- Bug causing `DataFrame.where` to not respect the `axis` parameter when the frame has a symmetric shape. (GH9736)
- Bug in `Table.select_column` where name is not preserved (GH10392)

- Bug in `offsets.generate_range` where `start` and `end` have finer precision than `offset` (GH9907)
- Bug in `pd.rolling_*` where `Series.name` would be lost in the output (GH10565)
- Bug in `stack` when index or columns are not unique. (GH10417)
- Bug in setting a `Panel` when an axis has a MultiIndex (GH10360)
- Bug in `USFederalHolidayCalendar` where `USMemorialDay` and `USMartinLutherKingJr` were incorrect (GH10278 and GH9760)
- Bug in `.sample()` where returned object, if set, gives unnecessary `SettingWithCopyWarning` (GH10738)
- Bug in `.sample()` where weights passed as `Series` were not aligned along axis before being treated positionally, potentially causing problems if weight indices were not aligned with sampled object. (GH10738)
- Regression fixed in (GH9311, GH6620, GH9345), where groupby with a datetime-like converting to float with certain aggregators (GH10979)
- Bug in `DataFrame.interpolate` with `axis=1` and `inplace=True` (GH10395)
- Bug in `io.sql.get_schema` when specifying multiple columns as primary key (GH10385).
- Bug in `groupby(sort=False)` with datetime-like `Categorical` raises `ValueError` (GH10505)
- Bug in `groupby(axis=1)` with `filter()` throws `IndexError` (GH11041)
- Bug in `test_categorical` on big-endian builds (GH10425)
- Bug in `Series.shift` and `DataFrame.shift` not supporting categorical data (GH9416)
- Bug in `Series.map` using categorical `Series` raises `AttributeError` (GH10324)
- Bug in `MultiIndex.get_level_values` including `Categorical` raises `AttributeError` (GH10460)
- Bug in `pd.get_dummies` with `sparse=True` not returning `SparseDataFrame` (GH10531)
- Bug in `Index` subtypes (such as `PeriodIndex`) not returning their own type for `.drop` and `.insert` methods (GH10620)
- Bug in `algos.outer_join_indexer` when `right` array is empty (GH10618)
- Bug in `filter` (regression from 0.16.0) and `transform` when grouping on multiple keys, one of which is datetime-like (GH10114)
- Bug in `to_datetime` and `to_timedelta` causing `Index` name to be lost (GH10875)
- Bug in `len(DataFrame.groupby)` causing `IndexError` when there's a column containing only NaNs (GH11016)
- Bug that caused segfault when resampling an empty Series (GH10228)
- Bug in `DatetimeIndex` and `PeriodIndex.value_counts` resets name from its result, but retains in result's `Index`. (GH10150)
- Bug in `pd.eval` using `numexpr` engine coerces 1 element numpy array to scalar (GH10546)
- Bug in `pd.concat` with `axis=0` when column is of dtype `category` (GH10177)
- Bug in `read_msgpack` where input type is not always checked (GH10369, GH10630)
- Bug in `pd.read_csv` with kwargs `index_col=False`, `index_col=['a', 'b']` or `dtype` (GH10413, GH10467, GH10577)
- Bug in `Series.from_csv` with `header` kwarg not setting the `Series.name` or the `Series.index.name` (GH10483)

- Bug in `groupby.var` which caused variance to be inaccurate for small float values (GH10448)
- Bug in `Series.plot(kind='hist')` Y Label not informative (GH10485)
- Bug in `read_csv` when using a converter which generates a `uint8` type (GH9266)
- Bug causes memory leak in time-series line and area plot (GH9003)
- Bug when setting a `Panel` sliced along the major or minor axes when the right-hand side is a `DataFrame` (GH11014)
- Bug that returns `None` and does not raise `NotImplementedError` when operator functions (e.g. `.add`) of `Panel` are not implemented (GH7692)
- Bug in line and kde plot cannot accept multiple colors when `subplots=True` (GH9894)
- Bug in `DataFrame.plot` raises `ValueError` when color name is specified by multiple characters (GH10387)
- Bug in left and right `align` of `Series` with `MultiIndex` may be inverted (GH10665)
- Bug in left and right `join` of with `MultiIndex` may be inverted (GH10741)
- Bug in `read_stata` when reading a file with a different order set in `columns` (GH10757)
- Bug in `Categorical` may not representing properly when category contains `tz` or `Period` (GH10713)
- Bug in `Categorical.__iter__` may not returning correct `datetime` and `Period` (GH10713)
- Bug in indexing with a `PeriodIndex` on an object with a `PeriodIndex` (GH4125)
- Bug in `read_csv` with `engine='c'`: EOF preceded by a comment, blank line, etc. was not handled correctly (GH10728, GH10548)
- Reading "famafrench" data via `DataReader` results in HTTP 404 error because of the website url is changed (GH10591).
- Bug in `read_msgpack` where DataFrame to decode has duplicate column names (GH9618)
- Bug in `io.common.get_filepath_or_buffer` which caused reading of valid S3 files to fail if the bucket also contained keys for which the user does not have read permission (GH10604)
- Bug in vectorised setting of timestamp columns with python `datetime.date` and numpy `datetime64` (GH10408, GH10412)
- Bug in `Index.take` may add unnecessary `freq` attribute (GH10791)
- Bug in `merge` with empty `DataFrame` may raise `IndexError` (GH10824)
- Bug in `to_latex` where unexpected keyword argument for some documented arguments (GH10888)
- Bug in indexing of large `DataFrame` where `IndexError` is uncaught (GH10645 and GH10692)
- Bug in `read_csv` when using the `nrows` or `chunksize` parameters if file contains only a header line (GH9535)
- Bug in serialization of `category` types in HDF5 in presence of alternate encodings. (GH10366)
- Bug in `pd.DataFrame` when constructing an empty DataFrame with a string dtype (GH9428)
- Bug in `pd.DataFrame.diff` when DataFrame is not consolidated (GH10907)
- Bug in `pd.unique` for arrays with the `datetime64` or `timedelta64` dtype that meant an array with object dtype was returned instead the original dtype (GH9431)
- Bug in `Timedelta` raising error when slicing from 0s (GH10583)

- Bug in `DatetimeIndex.take` and `TimedeltaIndex.take` may not raise `IndexError` against invalid index (GH10295)
- Bug in `Series([np.nan]).astype('M8[ms]')`, which now returns `Series([pd.NaT])` (GH10747)
- Bug in `PeriodIndex.order` reset freq (GH10295)
- Bug in `date_range` when `freq` divides `end` as nanos (GH10885)
- Bug in `iloc` allowing memory outside bounds of a Series to be accessed with negative integers (GH10779)
- Bug in `read_msgpack` where encoding is not respected (GH10581)
- Bug preventing access to the first index when using `iloc` with a list containing the appropriate negative integer (GH10547, GH10779)
- Bug in `TimedeltaIndex` formatter causing error while trying to save `DataFrame` with `TimedeltaIndex` using `to_csv` (GH10833)
- Bug in `DataFrame.where` when handling Series slicing (GH10218, GH9558)
- Bug where `pd.read_gbq` throws `ValueError` when Bigquery returns zero rows (GH10273)
- Bug in `to_json` which was causing segmentation fault when serializing 0-rank ndarray (GH9576)
- Bug in plotting functions may raise `IndexError` when plotted on `GridSpec` (GH10819)
- Bug in plot result may show unnecessary minor ticklabels (GH10657)
- Bug in `groupby` incorrect computation for aggregation on `DataFrame` with `NaT` (E.g `first`, `last`, `min`). (GH10590, GH11010)
- Bug when constructing `DataFrame` where passing a dictionary with only scalar values and specifying columns did not raise an error (GH10856)
- Bug in `.var()` causing roundoff errors for highly similar values (GH10242)
- Bug in `DataFrame.plot(subplots=True)` with duplicated columns outputs incorrect result (GH10962)
- Bug in `Index` arithmetic may result in incorrect class (GH10638)
- Bug in `date_range` results in empty if freq is negative annually, quarterly and monthly (GH11018)
- Bug in `DatetimeIndex` cannot infer negative freq (GH11018)
- Remove use of some deprecated numpy comparison operations, mainly in tests. (GH10569)
- Bug in `Index` dtype may not applied properly (GH11017)
- Bug in `io.gbq` when testing for minimum google api client version (GH10652)
- Bug in `DataFrame` construction from nested `dict` with `timedelta` keys (GH11129)
- Bug in `.fillna` against may raise `TypeError` when data contains datetime dtype (GH7095, GH11153)
- Bug in `.groupby` when number of keys to group by is same as length of index (GH11185)
- Bug in `convert_objects` where converted values might not be returned if all null and `coerce` (GH9589)
- Bug in `convert_objects` where `copy` keyword was not respected (GH9589)

Contributors

A total of 112 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Alex Rothberg
- Andrea Bedini +
- Andrew Rosenfeld
- Andy Hayden
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- Artemy Kolchinsky
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- Charlie Clark +
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- Siu Kwan Lam +
- Skipper Seabold
- Spencer Carrucciu +
- Stephan Hoyer
- Stephen Hoover +
- Stephen Pascoe +
- Terry Santegoeds +
- Thomas Grainger
- Tjerk Santegoeds +
- Tom Augspurger
- Vincent Davis +
- Winterflower +
- Yaroslav Halchenko
- Yuan Tang (Terry) +
- agijsberts
- ajcr +
- behzad nouri
- cel4
- chris-b1 +
- cyrusmaher +
- davidovitch +
- ganego +
- jreback
- juricast +
- larvian +
- maximilianr +
- msund +
- rekcahpassyla

- robertzk +
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- seth-p
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- springcoil +
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- tzinckgraf +

5.13 Version 0.16

5.13.1 Version 0.16.2 (June 12, 2015)

This is a minor bug-fix release from 0.16.1 and includes a large number of bug fixes along some new features (`pipe()` method), enhancements, and performance improvements.

We recommend that all users upgrade to this version.

Highlights include:

- A new `pipe` method, see *here*
- Documentation on how to use numba with *pandas*, see *here*

What's new in v0.16.2

- *New features*
  - *Pipe*
  - *Other enhancements*
- *API changes*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

New features

Pipe

We've introduced a new method `DataFrame.pipe()`. As suggested by the name, `pipe` should be used to pipe data through a chain of function calls. The goal is to avoid confusing nested function calls like

```
# df is a DataFrame
# f, g, and h are functions that take and return DataFrames
f(g(h(df), arg1=1), arg2=2, arg3=3)  # noqa F821
```

The logic flows from inside out, and function names are separated from their keyword arguments. This can be rewritten as

```
(
    df.pipe(h)  # noqa F821
    .pipe(g, arg1=1)  # noqa F821
    .pipe(f, arg2=2, arg3=3)  # noqa F821
)
```

Now both the code and the logic flow from top to bottom. Keyword arguments are next to their functions. Overall the code is much more readable.

In the example above, the functions `f`, `g`, and `h` each expected the DataFrame as the first positional argument. When the function you wish to apply takes its data anywhere other than the first argument, pass a tuple of `(function, keyword)` indicating where the DataFrame should flow. For example:

```
In [1]: import statsmodels.formula.api as sm

In [2]: bb = pd.read_csv("data/baseball.csv", index_col="id")

# sm.ols takes (formula, data)
In [3]: (
   ...:     bb.query("h > 0")
   ...:     .assign(ln_h=lambda df: np.log(df.h))
   ...:     .pipe((sm.ols, "data"), "hr ~ ln_h + year + g + C(lg)")
   ...:     .fit()
   ...:     .summary()
   ...: )
   ...:
Out[3]:
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                     hr   R-squared:                       0.685
Model:                            OLS   Adj. R-squared:                  0.665
Method:                 Least Squares   F-statistic:                     34.28
Date:                Tue, 09 Feb 2021   Prob (F-statistic):           3.48e-15
Time:                        11:34:44   Log-Likelihood:                -205.92
No. Observations:                  68   AIC:                             421.8
Df Residuals:                      63   BIC:                             432.9
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   -8484.7720   4664.146     -1.819      0.074   -1.78e+04     835.780
C(lg)[T.NL]    -2.2736      1.325     -1.716      0.091      -4.922       0.375
ln_h           -1.3542      0.875     -1.547      0.127      -3.103       0.395
year            4.2277      2.324      1.819      0.074      -0.417       8.872
g               0.1841      0.029      6.258      0.000       0.125       0.243
==============================================================================
Omnibus:                       10.875   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               17.298
Skew:                           0.537   Prob(JB):                     0.000175
Kurtosis:                       5.225   Cond. No.                     1.49e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly␣
↪specified.
```

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```
[2] The condition number is large, 1.49e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

The pipe method is inspired by unix pipes, which stream text through processes. More recently dplyr and magrittr have introduced the popular `(%>%)` pipe operator for R.

See the *documentation* for more. (GH10129)

Other enhancements

- Added `rsplit` to Index/Series StringMethods (GH10303)
- Removed the hard-coded size limits on the `DataFrame` HTML representation in the IPython notebook, and leave this to IPython itself (only for IPython v3.0 or greater). This eliminates the duplicate scroll bars that appeared in the notebook with large frames (GH10231).

  Note that the notebook has a `toggle output scrolling` feature to limit the display of very large frames (by clicking left of the output). You can also configure the way DataFrames are displayed using the pandas options, see here *here*.
- `axis` parameter of `DataFrame.quantile` now accepts also `index` and `column`. (GH9543)

API changes

- `Holiday` now raises `NotImplementedError` if both `offset` and `observance` are used in the constructor instead of returning an incorrect result (GH10217).

Performance improvements

- Improved `Series.resample` performance with `dtype=datetime64[ns]` (GH7754)
- Increase performance of `str.split` when `expand=True` (GH10081)

Bug fixes

- Bug in `Series.hist` raises an error when a one row `Series` was given (GH10214)
- Bug where `HDFStore.select` modifies the passed columns list (GH7212)
- Bug in `Categorical` repr with `display.width` of `None` in Python 3 (GH10087)
- Bug in `to_json` with certain orients and a `CategoricalIndex` would segfault (GH10317)
- Bug where some of the nan functions do not have consistent return dtypes (GH10251)
- Bug in `DataFrame.quantile` on checking that a valid axis was passed (GH9543)
- Bug in `groupby.apply` aggregation for `Categorical` not preserving categories (GH10138)
- Bug in `to_csv` where `date_format` is ignored if the `datetime` is fractional (GH10209)
- Bug in `DataFrame.to_json` with mixed data types (GH10289)
- Bug in cache updating when consolidating (GH10264)
- Bug in `mean()` where integer dtypes can overflow (GH10172)

- Bug where `Panel.from_dict` does not set dtype when specified (GH10058)
- Bug in `Index.union` raises `AttributeError` when passing array-likes. (GH10149)
- Bug in `Timestamp`'s' `microsecond`, `quarter`, `dayofyear`, `week` and `daysinmonth` properties return `np.int` type, not built-in `int`. (GH10050)
- Bug in `NaT` raises `AttributeError` when accessing to `daysinmonth`, `dayofweek` properties. (GH10096)
- Bug in Index repr when using the `max_seq_items=None` setting (GH10182).
- Bug in getting timezone data with `dateutil` on various platforms (GH9059, GH8639, GH9663, GH10121)
- Bug in displaying datetimes with mixed frequencies; display 'ms' datetimes to the proper precision. (GH10170)
- Bug in `setitem` where type promotion is applied to the entire block (GH10280)
- Bug in `Series` arithmetic methods may incorrectly hold names (GH10068)
- Bug in `GroupBy.get_group` when grouping on multiple keys, one of which is categorical. (GH10132)
- Bug in `DatetimeIndex` and `TimedeltaIndex` names are lost after timedelta arithmetic (GH9926)
- Bug in `DataFrame` construction from nested `dict` with `datetime64` (GH10160)
- Bug in `Series` construction from `dict` with `datetime64` keys (GH9456)
- Bug in `Series.plot(label="LABEL")` not correctly setting the label (GH10119)
- Bug in `plot` not defaulting to matplotlib `axes.grid` setting (GH9792)
- Bug causing strings containing an exponent, but no decimal to be parsed as `int` instead of `float` in `engine='python'` for the `read_csv` parser (GH9565)
- Bug in `Series.align` resets `name` when `fill_value` is specified (GH10067)
- Bug in `read_csv` causing index name not to be set on an empty DataFrame (GH10184)
- Bug in `SparseSeries.abs` resets `name` (GH10241)
- Bug in `TimedeltaIndex` slicing may reset freq (GH10292)
- Bug in `GroupBy.get_group` raises `ValueError` when group key contains `NaT` (GH6992)
- Bug in `SparseSeries` constructor ignores input data name (GH10258)
- Bug in `Categorical.remove_categories` causing a `ValueError` when removing the `NaN` category if underlying dtype is floating-point (GH10156)
- Bug where infer_freq infers time rule (WOM-5XXX) unsupported by to_offset (GH9425)
- Bug in `DataFrame.to_hdf()` where table format would raise a seemingly unrelated error for invalid (non-string) column names. This is now explicitly forbidden. (GH9057)
- Bug to handle masking empty `DataFrame` (GH10126).
- Bug where MySQL interface could not handle numeric table/column names (GH10255)
- Bug in `read_csv` with a `date_parser` that returned a `datetime64` array of other time resolution than `[ns]` (GH10245)
- Bug in `Panel.apply` when the result has ndim=0 (GH10332)
- Bug in `read_hdf` where `auto_close` could not be passed (GH9327).
- Bug in `read_hdf` where open stores could not be used (GH10330).

- Bug in adding empty `DataFrames`, now results in a `DataFrame` that `.equals` an empty `DataFrame` (GH10181).
- Bug in `to_hdf` and `HDFStore` which did not check that complib choices were valid (GH4582, GH8874).

Contributors

A total of 34 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Andrew Rosenfeld
- Artemy Kolchinsky
- Bernard Willers +
- Christer van der Meeren
- Christian Hudon +
- Constantine Glen Evans +
- Daniel Julius Lasiman +
- Evan Wright
- Francesco Brundu +
- Gaëtan de Menten +
- Jake VanderPlas
- James Hiebert +
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- lexual
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- scls19fr
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5.13.2 Version 0.16.1 (May 11, 2015)

This is a minor bug-fix release from 0.16.0 and includes a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Support for a `CategoricalIndex`, a category based index, see *here*
- New section on how-to-contribute to *pandas*, see *here*
- Revised "Merge, join, and concatenate" documentation, including graphical examples to make it easier to understand each operations, see *here*
- New method `sample` for drawing random samples from Series, DataFrames and Panels. See *here*
- The default `Index` printing has changed to a more uniform format, see *here*
- `BusinessHour` datetime-offset is now supported, see *here*
- Further enhancement to the `.str` accessor to make string operations easier, see *here*

What's new in v0.16.1

- *Enhancements*
  - *CategoricalIndex*
  - *Sample*
  - *String methods enhancements*
  - *Other enhancements*
- *API changes*
  - *Deprecations*
- *Index representation*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

Warning: In pandas 0.17.0, the sub-package `pandas.io.data` will be removed in favor of a separately installable package (GH8961).

Enhancements

CategoricalIndex

We introduce a `CategoricalIndex`, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a `Categorical` (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a `DataFrame/Series` with a `category` dtype would convert this to regular object-based `Index`.

```
In [1]: df = pd.DataFrame({'A': np.arange(6),
   ...:                    'B': pd.Series(list('aabbca'))
   ...:                           .astype('category', categories=list('cab'))
   ...:                    })
   ...:

In [2]: df
Out[2]:
   A  B
0  0  a
1  1  a
2  2  b
3  3  b
4  4  c
5  5  a

In [3]: df.dtypes
Out[3]:
A       int64
B    category
dtype: object

In [4]: df.B.cat.categories
Out[4]: Index(['c', 'a', 'b'], dtype='object')
```

setting the index, will create a `CategoricalIndex`

```
In [5]: df2 = df.set_index('B')

In [6]: df2.index
Out[6]: CategoricalIndex(['a', 'a', 'b', 'b', 'c', 'a'], categories=['c', 'a', 'b'],␣
↪ordered=False, name='B', dtype='category')
```

indexing with `__getitem__/.iloc/.loc/.ix` works similarly to an Index with duplicates. The indexers MUST be in the category or the operation will raise.

```
In [7]: df2.loc['a']
Out[7]:
   A
B
a  0
a  1
a  5
```

and preserves the `CategoricalIndex`

```
In [8]: df2.loc['a'].index
Out[8]: CategoricalIndex(['a', 'a', 'a'], categories=['c', 'a', 'b'], ordered=False,␣
↪name='B', dtype='category')
```

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sorting will order by the order of the categories

```
In [9]: df2.sort_index()
Out[9]:
   A
B
c  4
a  0
a  1
a  5
b  2
b  3
```

groupby operations on the index will preserve the index nature as well

```
In [10]: df2.groupby(level=0).sum()
Out[10]:
   A
B
c  4
a  6
b  5

In [11]: df2.groupby(level=0).sum().index
Out[11]: CategoricalIndex(['c', 'a', 'b'], categories=['c', 'a', 'b'], ordered=False,␣
↪name='B', dtype='category')
```

reindexing operations, will return a resulting index based on the type of the passed indexer, meaning that passing a list will return a plain-old-`Index`; indexing with a `Categorical` will return a `CategoricalIndex`, indexed according to the categories of the PASSED `Categorical` dtype. This allows one to arbitrarily index these even with values NOT in the categories, similarly to how you can reindex ANY pandas index.

```
In [12]: df2.reindex(['a', 'e'])
Out[12]:
     A
B
a  0.0
a  1.0
a  5.0
e  NaN

In [13]: df2.reindex(['a', 'e']).index
Out[13]: pd.Index(['a', 'a', 'a', 'e'], dtype='object', name='B')

In [14]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde')))
Out[14]:
     A
B
a  0.0
a  1.0
a  5.0
e  NaN

In [15]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde'))).index
Out[15]: pd.CategoricalIndex(['a', 'a', 'a', 'e'],
```

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```
                                categories=['a', 'b', 'c', 'd', 'e'],
                                ordered=False, name='B',
                                dtype='category')
```

See the *documentation* for more. (GH7629, GH10038, GH10039)

Sample

Series, DataFrames, and Panels now have a new method: `sample()`. The method accepts a specific number of rows or columns to return, or a fraction of the total number or rows or columns. It also has options for sampling with or without replacement, for passing in a column for weights for non-uniform sampling, and for setting seed values to facilitate replication. (GH2419)

```
In [1]: example_series = pd.Series([0, 1, 2, 3, 4, 5])

# When no arguments are passed, returns 1
In [2]: example_series.sample()
Out[2]:
3    3
Length: 1, dtype: int64

# One may specify either a number of rows:
In [3]: example_series.sample(n=3)
Out[3]:
2    2
1    1
0    0
Length: 3, dtype: int64

# Or a fraction of the rows:
In [4]: example_series.sample(frac=0.5)
Out[4]:
1    1
5    5
3    3
Length: 3, dtype: int64

# weights are accepted.
In [5]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [6]: example_series.sample(n=3, weights=example_weights)
Out[6]:
2    2
4    4
3    3
Length: 3, dtype: int64

# weights will also be normalized if they do not sum to one,
# and missing values will be treated as zeros.
In [7]: example_weights2 = [0.5, 0, 0, 0, None, np.nan]

In [8]: example_series.sample(n=1, weights=example_weights2)
Out[8]:
0    0
Length: 1, dtype: int64
```

When applied to a DataFrame, one may pass the name of a column to specify sampling weights when sampling from rows.

```
In [9]: df = pd.DataFrame({"col1": [9, 8, 7, 6], "weight_column": [0.5, 0.4, 0.1, 0]})

In [10]: df.sample(n=3, weights="weight_column")
Out[10]:
   col1  weight_column
0     9            0.5
1     8            0.4
2     7            0.1

[3 rows x 2 columns]
```

String methods enhancements

Continuing from v0.16.0, the following enhancements make string operations easier and more consistent with standard python string operations.

- Added `StringMethods` (`.str` accessor) to `Index` (GH9068)

  The `.str` accessor is now available for both `Series` and `Index`.

  ```
  In [11]: idx = pd.Index([" jack", "jill ", " jesse ", "frank"])

  In [12]: idx.str.strip()
  Out[12]: Index(['jack', 'jill', 'jesse', 'frank'], dtype='object')
  ```

  One special case for the `.str` accessor on `Index` is that if a string method returns `bool`, the `.str` accessor will return a `np.array` instead of a boolean `Index` (GH8875). This enables the following expression to work naturally:

  ```
  In [13]: idx = pd.Index(["a1", "a2", "b1", "b2"])

  In [14]: s = pd.Series(range(4), index=idx)

  In [15]: s
  Out[15]:
  a1    0
  a2    1
  b1    2
  b2    3
  Length: 4, dtype: int64

  In [16]: idx.str.startswith("a")
  Out[16]: array([ True,  True, False, False])

  In [17]: s[s.index.str.startswith("a")]
  Out[17]:
  a1    0
  a2    1
  Length: 2, dtype: int64
  ```

- The following new methods are accessible via `.str` accessor to apply the function to each values. (GH9766, GH9773, GH10031, GH10045, GH10052)

		Methods		
capitalize()	swapcase()	normalize()	partition()	rpartition()
index()	rindex()	translate()		

- split now takes expand keyword to specify whether to expand dimensionality. return_type is deprecated. (GH9847)

```
In [18]: s = pd.Series(["a,b", "a,c", "b,c"])

# return Series
In [19]: s.str.split(",")
Out[19]:
0    [a, b]
1    [a, c]
2    [b, c]
Length: 3, dtype: object

# return DataFrame
In [20]: s.str.split(",", expand=True)
Out[20]:
   0  1
0  a  b
1  a  c
2  b  c

[3 rows x 2 columns]

In [21]: idx = pd.Index(["a,b", "a,c", "b,c"])

# return Index
In [22]: idx.str.split(",")
Out[22]: Index([['a', 'b'], ['a', 'c'], ['b', 'c']], dtype='object')

# return MultiIndex
In [23]: idx.str.split(",", expand=True)
Out[23]:
MultiIndex([('a', 'b'),
            ('a', 'c'),
            ('b', 'c')],
           )
```

- Improved extract and get_dummies methods for Index.str (GH9980)

Other enhancements

- BusinessHour offset is now supported, which represents business hours starting from 09:00 - 17:00 on BusinessDay by default. See *Here* for details. (GH7905)

```
In [24]: pd.Timestamp("2014-08-01 09:00") + pd.tseries.offsets.BusinessHour()
Out[24]: Timestamp('2014-08-01 10:00:00')

In [25]: pd.Timestamp("2014-08-01 07:00") + pd.tseries.offsets.BusinessHour()
Out[25]: Timestamp('2014-08-01 10:00:00')
```

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```
In [26]: pd.Timestamp("2014-08-01 16:30") + pd.tseries.offsets.BusinessHour()
Out[26]: Timestamp('2014-08-04 09:30:00')
```

- `DataFrame.diff` now takes an `axis` parameter that determines the direction of differencing (GH9727)
- Allow `clip`, `clip_lower`, and `clip_upper` to accept array-like arguments as thresholds (This is a regression from 0.11.0). These methods now have an `axis` parameter which determines how the Series or DataFrame will be aligned with the threshold(s). (GH6966)
- `DataFrame.mask()` and `Series.mask()` now support same keywords as `where` (GH8801)
- `drop` function can now accept `errors` keyword to suppress `ValueError` raised when any of label does not exist in the target data. (GH6736)

```
In [27]: df = pd.DataFrame(np.random.randn(3, 3), columns=["A", "B", "C"])

In [28]: df.drop(["A", "X"], axis=1, errors="ignore")
Out[28]:
          B         C
0 -0.706771 -1.039575
1 -0.424972  0.567020
2 -1.087401 -0.673690

[3 rows x 2 columns]
```

- Add support for separating years and quarters using dashes, for example 2014-Q1. (GH9688)
- Allow conversion of values with dtype `datetime64` or `timedelta64` to strings using `astype(str)` (GH9757)
- `get_dummies` function now accepts `sparse` keyword. If set to `True`, the return `DataFrame` is sparse, e.g. `SparseDataFrame`. (GH8823)
- `Period` now accepts `datetime64` as value input. (GH9054)
- Allow timedelta string conversion when leading zero is missing from time definition, ie `0:00:00` vs `00:00:00`. (GH9570)
- Allow `Panel.shift` with `axis='items'` (GH9890)
- Trying to write an excel file now raises `NotImplementedError` if the `DataFrame` has a `MultiIndex` instead of writing a broken Excel file. (GH9794)
- Allow `Categorical.add_categories` to accept `Series` or `np.array`. (GH9927)
- Add/delete `str/dt/cat` accessors dynamically from `__dir__`. (GH9910)
- Add `normalize` as a `dt` accessor method. (GH10047)
- `DataFrame` and `Series` now have `_constructor_expanddim` property as overridable constructor for one higher dimensionality data. This should be used only when it is really needed, see *here*
- `pd.lib.infer_dtype` now returns `'bytes'` in Python 3 where appropriate. (GH10032)

API changes

- When passing in an ax to `df.plot( ..., ax=ax)`, the `sharex` kwarg will now default to `False`. The result is that the visibility of xlabels and xticklabels will not anymore be changed. You have to do that by yourself for the right axes in your figure or set `sharex=True` explicitly (but this changes the visible for all axes in the figure, not only the one which is passed in!). If pandas creates the subplots itself (e.g. no passed in `ax` kwarg), then the default is still `sharex=True` and the visibility changes are applied.
- *`assign()`* now inserts new columns in alphabetical order. Previously the order was arbitrary. (GH9777)
- By default, `read_csv` and `read_table` will now try to infer the compression type based on the file extension. Set `compression=None` to restore the previous behavior (no decompression). (GH9770)

Deprecations

- `Series.str.split`'s `return_type` keyword was removed in favor of `expand` (GH9847)

Index representation

The string representation of `Index` and its sub-classes have now been unified. These will show a single-line display if there are few values; a wrapped multi-line display for a lot of values (but less than `display.max_seq_items`; if lots of items (> `display.max_seq_items`) will show a truncated display (the head and tail of the data). The formatting for `MultiIndex` is unchanged (a multi-line wrapped display). The display width responds to the option `display.max_seq_items`, which is defaulted to 100. (GH6482)

Previous behavior

```
In [2]: pd.Index(range(4), name='foo')
Out[2]: Int64Index([0, 1, 2, 3], dtype='int64')

In [3]: pd.Index(range(104), name='foo')
Out[3]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18,␣
↪19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,␣
↪40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60,␣
↪61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81,␣
↪82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, ...], dtype=
↪'int64')

In [4]: pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')
Out[4]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-01-04 00:00:00-05:00]
Length: 4, Freq: D, Timezone: US/Eastern

In [5]: pd.date_range('20130101', periods=104, name='foo', tz='US/Eastern')
Out[5]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-04-14 00:00:00-04:00]
Length: 104, Freq: D, Timezone: US/Eastern
```

New behavior

```
In [29]: pd.set_option("display.width", 80)

In [30]: pd.Index(range(4), name="foo")
```

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```
Out[30]: RangeIndex(start=0, stop=4, step=1, name='foo')

In [31]: pd.Index(range(30), name="foo")
Out[31]: RangeIndex(start=0, stop=30, step=1, name='foo')

In [32]: pd.Index(range(104), name="foo")
Out[32]: RangeIndex(start=0, stop=104, step=1, name='foo')

In [33]: pd.CategoricalIndex(["a", "bb", "ccc", "dddd"], ordered=True, name="foobar")
Out[33]: CategoricalIndex(['a', 'bb', 'ccc', 'dddd'], categories=['a', 'bb', 'ccc',
↪'dddd'], ordered=True, name='foobar', dtype='category')

In [34]: pd.CategoricalIndex(["a", "bb", "ccc", "dddd"] * 10, ordered=True, name=
↪"foobar")
Out[34]:
CategoricalIndex(['a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a',
                  'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb',
                  'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc',
                  'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd',
                  'a', 'bb', 'ccc', 'dddd'],
                 categories=['a', 'bb', 'ccc', 'dddd'], ordered=True, name='foobar',␣
↪dtype='category')

In [35]: pd.CategoricalIndex(["a", "bb", "ccc", "dddd"] * 100, ordered=True, name=
↪"foobar")
Out[35]:
CategoricalIndex(['a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a',
                  'bb',
                  ...
                  'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc',
                  'dddd'],
                 categories=['a', 'bb', 'ccc', 'dddd'], ordered=True, name='foobar',␣
↪dtype='category', length=400)

In [36]: pd.date_range("20130101", periods=4, name="foo", tz="US/Eastern")
Out[36]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
               '2013-01-03 00:00:00-05:00', '2013-01-04 00:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', name='foo', freq='D')

In [37]: pd.date_range("20130101", periods=25, freq="D")
Out[37]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
               '2013-01-09', '2013-01-10', '2013-01-11', '2013-01-12',
               '2013-01-13', '2013-01-14', '2013-01-15', '2013-01-16',
               '2013-01-17', '2013-01-18', '2013-01-19', '2013-01-20',
               '2013-01-21', '2013-01-22', '2013-01-23', '2013-01-24',
               '2013-01-25'],
              dtype='datetime64[ns]', freq='D')

In [38]: pd.date_range("20130101", periods=104, name="foo", tz="US/Eastern")
Out[38]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
               '2013-01-03 00:00:00-05:00', '2013-01-04 00:00:00-05:00',
               '2013-01-05 00:00:00-05:00', '2013-01-06 00:00:00-05:00',
               '2013-01-07 00:00:00-05:00', '2013-01-08 00:00:00-05:00',
```

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```
               '2013-01-09 00:00:00-05:00', '2013-01-10 00:00:00-05:00',
               ...
               '2013-04-05 00:00:00-04:00', '2013-04-06 00:00:00-04:00',
               '2013-04-07 00:00:00-04:00', '2013-04-08 00:00:00-04:00',
               '2013-04-09 00:00:00-04:00', '2013-04-10 00:00:00-04:00',
               '2013-04-11 00:00:00-04:00', '2013-04-12 00:00:00-04:00',
               '2013-04-13 00:00:00-04:00', '2013-04-14 00:00:00-04:00'],
              dtype='datetime64[ns, US/Eastern]', name='foo', length=104, freq='D')
```

Performance improvements

- Improved csv write performance with mixed dtypes, including datetimes by up to 5x (GH9940)
- Improved csv write performance generally by 2x (GH9940)
- Improved the performance of `pd.lib.max_len_string_array` by 5-7x (GH10024)

Bug fixes

- Bug where labels did not appear properly in the legend of `DataFrame.plot()`, passing `label=` arguments works, and Series indices are no longer mutated. (GH9542)
- Bug in json serialization causing a segfault when a frame had zero length. (GH9805)
- Bug in `read_csv` where missing trailing delimiters would cause segfault. (GH5664)
- Bug in retaining index name on appending (GH9862)
- Bug in `scatter_matrix` draws unexpected axis ticklabels (GH5662)
- Fixed bug in `StataWriter` resulting in changes to input `DataFrame` upon save (GH9795).
- Bug in `transform` causing length mismatch when null entries were present and a fast aggregator was being used (GH9697)
- Bug in `equals` causing false negatives when block order differed (GH9330)
- Bug in grouping with multiple `pd.Grouper` where one is non-time based (GH10063)
- Bug in `read_sql_table` error when reading postgres table with timezone (GH7139)
- Bug in `DataFrame` slicing may not retain metadata (GH9776)
- Bug where `TimdeltaIndex` were not properly serialized in fixed `HDFStore` (GH9635)
- Bug with `TimedeltaIndex` constructor ignoring `name` when given another `TimedeltaIndex` as data (GH10025).
- Bug in `DataFrameFormatter._get_formatted_index` with not applying `max_colwidth` to the `DataFrame` index (GH7856)
- Bug in `.loc` with a read-only ndarray data source (GH10043)
- Bug in `groupby.apply()` that would raise if a passed user defined function either returned only `None` (for all input). (GH9685)
- Always use temporary files in pytables tests (GH9992)
- Bug in plotting continuously using `secondary_y` may not show legend properly. (GH9610, GH9779)

- Bug in `DataFrame.plot(kind="hist")` results in `TypeError` when `DataFrame` contains non-numeric columns (GH9853)
- Bug where repeated plotting of `DataFrame` with a `DatetimeIndex` may raise `TypeError` (GH9852)
- Bug in `setup.py` that would allow an incompat cython version to build (GH9827)
- Bug in plotting `secondary_y` incorrectly attaches `right_ax` property to secondary axes specifying itself recursively. (GH9861)
- Bug in `Series.quantile` on empty Series of type `Datetime` or `Timedelta` (GH9675)
- Bug in `where` causing incorrect results when upcasting was required (GH9731)
- Bug in `FloatArrayFormatter` where decision boundary for displaying "small" floats in decimal format is off by one order of magnitude for a given display.precision (GH9764)
- Fixed bug where `DataFrame.plot()` raised an error when both `color` and `style` keywords were passed and there was no color symbol in the style strings (GH9671)
- Not showing a `DeprecationWarning` on combining list-likes with an `Index` (GH10083)
- Bug in `read_csv` and `read_table` when using `skip_rows` parameter if blank lines are present. (GH9832)
- Bug in `read_csv()` interprets `index_col=True` as `1` (GH9798)
- Bug in index equality comparisons using == failing on Index/MultiIndex type incompatibility (GH9785)
- Bug in which `SparseDataFrame` could not take `nan` as a column name (GH8822)
- Bug in `to_msgpack` and `read_msgpack` zlib and blosc compression support (GH9783)
- Bug `GroupBy.size` doesn't attach index name properly if grouped by `TimeGrouper` (GH9925)
- Bug causing an exception in slice assignments because `length_of_indexer` returns wrong results (GH9995)
- Bug in csv parser causing lines with initial white space plus one non-space character to be skipped. (GH9710)
- Bug in C csv parser causing spurious NaNs when data started with newline followed by white space. (GH10022)
- Bug causing elements with a null group to spill into the final group when grouping by a `Categorical` (GH9603)
- Bug where .iloc and .loc behavior is not consistent on empty dataframes (GH9964)
- Bug in invalid attribute access on a `TimedeltaIndex` incorrectly raised `ValueError` instead of `AttributeError` (GH9680)
- Bug in unequal comparisons between categorical data and a scalar, which was not in the categories (e.g. `Series(Categorical(list("abc"), ordered=True)) > "d"`. This returned `False` for all elements, but now raises a `TypeError`. Equality comparisons also now return `False` for == and `True` for `!=`. (GH9848)
- Bug in DataFrame `__setitem__` when right hand side is a dictionary (GH9874)
- Bug in `where` when dtype is `datetime64/timedelta64`, but dtype of other is not (GH9804)
- Bug in `MultiIndex.sortlevel()` results in unicode level name breaks (GH9856)
- Bug in which `groupby.transform` incorrectly enforced output dtypes to match input dtypes. (GH9807)
- Bug in `DataFrame` constructor when `columns` parameter is set, and `data` is an empty list (GH9939)
- Bug in bar plot with `log=True` raises `TypeError` if all values are less than 1 (GH9905)
- Bug in horizontal bar plot ignores `log=True` (GH9905)

- Bug in PyTables queries that did not return proper results using the index (GH8265, GH9676)
- Bug where dividing a dataframe containing values of type `Decimal` by another `Decimal` would raise. (GH9787)
- Bug where using DataFrames asfreq would remove the name of the index. (GH9885)
- Bug causing extra index point when resample BM/BQ (GH9756)
- Changed caching in `AbstractHolidayCalendar` to be at the instance level rather than at the class level as the latter can result in unexpected behaviour. (GH9552)
- Fixed latex output for MultiIndexed dataframes (GH9778)
- Bug causing an exception when setting an empty range using `DataFrame.loc` (GH9596)
- Bug in hiding ticklabels with subplots and shared axes when adding a new plot to an existing grid of axes (GH9158)
- Bug in `transform` and `filter` when grouping on a categorical variable (GH9921)
- Bug in `transform` when groups are equal in number and dtype to the input index (GH9700)
- Google BigQuery connector now imports dependencies on a per-method basis.(GH9713)
- Updated BigQuery connector to no longer use deprecated `oauth2client.tools.run()` (GH8327)
- Bug in subclassed `DataFrame`. It may not return the correct class, when slicing or subsetting it. (GH9632)
- Bug in `.median()` where non-float null values are not handled correctly (GH10040)
- Bug in Series.fillna() where it raises if a numerically convertible string is given (GH10092)

Contributors

A total of 58 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Andy Hayden
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- sinhrks

5.13.3 Version 0.16.0 (March 22, 2015)

This is a major release from 0.15.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `DataFrame.assign` method, see *here*
- `Series.to_coo/from_coo` methods to interact with `scipy.sparse`, see *here*
- Backwards incompatible change to `Timedelta` to conform the `.seconds` attribute with `datetime.timedelta`, see *here*
- Changes to the `.loc` slicing API to conform with the behavior of `.ix` see *here*
- Changes to the default for ordering in the `Categorical` constructor, see *here*
- Enhancement to the `.str` accessor to make string operations easier, see *here*
- The `pandas.tools.rplot`, `pandas.sandbox.qtpandas` and `pandas.rpy` modules are deprecated. We refer users to external packages like seaborn, pandas-qt and rpy2 for similar or equivalent functionality, see *here*

Check the *API Changes* and *deprecations* before updating.

What's new in v0.16.0

- *New features*
  - *DataFrame assign*
  - *Interaction with scipy.sparse*
  - *String methods enhancements*
  - *Other enhancements*
- *Backwards incompatible API changes*
  - *Changes in timedelta*
  - *Indexing changes*
  - *Categorical changes*
  - *Other API changes*
  - *Deprecations*

- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

New features

DataFrame assign

Inspired by dplyr's `mutate` verb, DataFrame has a new *`assign()`* method. The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. The new values are inserted, and the entire DataFrame (with all original and new columns) is returned.

```
In [1]: iris = pd.read_csv('data/iris.data')

In [2]: iris.head()
Out[2]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name
0          5.1         3.5          1.4         0.2  Iris-setosa
1          4.9         3.0          1.4         0.2  Iris-setosa
2          4.7         3.2          1.3         0.2  Iris-setosa
3          4.6         3.1          1.5         0.2  Iris-setosa
4          5.0         3.6          1.4         0.2  Iris-setosa

[5 rows x 5 columns]

In [3]: iris.assign(sepal_ratio=iris['SepalWidth'] / iris['SepalLength']).head()
Out[3]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa     0.686275
1          4.9         3.0          1.4         0.2  Iris-setosa     0.612245
2          4.7         3.2          1.3         0.2  Iris-setosa     0.680851
3          4.6         3.1          1.5         0.2  Iris-setosa     0.673913
4          5.0         3.6          1.4         0.2  Iris-setosa     0.720000

[5 rows x 6 columns]
```

Above was an example of inserting a precomputed value. We can also pass in a function to be evaluated.

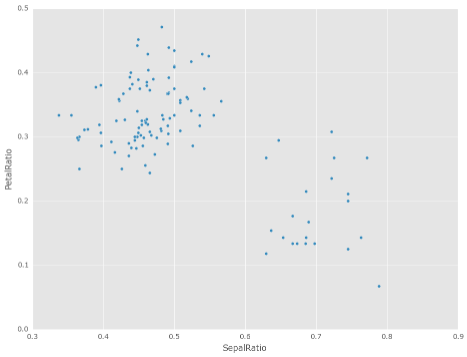
```
In [4]: iris.assign(sepal_ratio=lambda x: (x['SepalWidth']
   ...:                                    / x['SepalLength'])).head()
   ...:
Out[4]:
   SepalLength  SepalWidth  PetalLength  PetalWidth         Name  sepal_ratio
0          5.1         3.5          1.4         0.2  Iris-setosa     0.686275
1          4.9         3.0          1.4         0.2  Iris-setosa     0.612245
2          4.7         3.2          1.3         0.2  Iris-setosa     0.680851
3          4.6         3.1          1.5         0.2  Iris-setosa     0.673913
4          5.0         3.6          1.4         0.2  Iris-setosa     0.720000

[5 rows x 6 columns]
```

The power of `assign` comes when used in chains of operations. For example, we can limit the DataFrame to just those with a Sepal Length greater than 5, calculate the ratio, and plot

```
In [5]: iris = pd.read_csv('data/iris.data')

In [6]: (iris.query('SepalLength > 5')
   ...:       .assign(SepalRatio=lambda x: x.SepalWidth / x.SepalLength,
   ...:               PetalRatio=lambda x: x.PetalWidth / x.PetalLength)
   ...:       .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))
   ...:
Out[6]: <AxesSubplot:xlabel='SepalRatio', ylabel='PetalRatio'>
```



See the *documentation* for more. (GH9229)

Interaction with scipy.sparse

Added `SparseSeries.to_coo()` and `SparseSeries.from_coo()` methods (GH8048) for converting to and from `scipy.sparse.coo_matrix` instances (see *here*). For example, given a SparseSeries with MultiIndex we can convert to a `scipy.sparse.coo_matrix` by specifying the row and column labels as index levels:

```
s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
s.index = pd.MultiIndex.from_tuples([(1, 2, 'a', 0),
                                     (1, 2, 'a', 1),
                                     (1, 1, 'b', 0),
                                     (1, 1, 'b', 1),
                                     (2, 1, 'b', 0),
                                     (2, 1, 'b', 1)],
                                    names=['A', 'B', 'C', 'D'])

s

# SparseSeries
ss = s.to_sparse()
ss

A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
                             column_levels=['C', 'D'],
                             sort_labels=False)

A
A.todense()
rows
columns
```

The from_coo method is a convenience method for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`:

```
from scipy import sparse
A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
                      shape=(3, 4))
A
A.todense()

ss = pd.SparseSeries.from_coo(A)
ss
```

String methods enhancements

- Following new methods are accessible via `.str` accessor to apply the function to each values. This is intended to make it more consistent with standard methods on strings. (GH9282, GH9352, GH9386, GH9387, GH9439)

		Methods		
`isalnum()`	`isalpha()`	`isdigit()`	`isdigit()`	`isspace()`
`islower()`	`isupper()`	`istitle()`	`isnumeric()`	`isdecimal()`
`find()`	`rfind()`	`ljust()`	`rjust()`	`zfill()`

```
In [7]: s = pd.Series(['abcd', '3456', 'EFGH'])

In [8]: s.str.isalpha()
Out[8]:
0     True
1    False
2     True
Length: 3, dtype: bool

In [9]: s.str.find('ab')
Out[9]:
0    0
1   -1
2   -1
Length: 3, dtype: int64
```

- *`Series.str.pad()`* and *`Series.str.center()`* now accept `fillchar` option to specify filling character (GH9352)

```
In [10]: s = pd.Series(['12', '300', '25'])

In [11]: s.str.pad(5, fillchar='_')
Out[11]:
0    ___12
1    __300
2    ___25
Length: 3, dtype: object
```

- Added *`Series.str.slice_replace()`*, which previously raised `NotImplementedError` (GH8888)

```
In [12]: s = pd.Series(['ABCD', 'EFGH', 'IJK'])
```

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```
In [13]: s.str.slice_replace(1, 3, 'X')
Out[13]:
0    AXD
1    EXH
2     IX
Length: 3, dtype: object

# replaced with empty char
In [14]: s.str.slice_replace(0, 1)
Out[14]:
0    BCD
1    FGH
2     JK
Length: 3, dtype: object
```

Other enhancements

- Reindex now supports `method='nearest'` for frames or series with a monotonic increasing or decreasing index (GH9258):

```
In [15]: df = pd.DataFrame({'x': range(5)})

In [16]: df.reindex([0.2, 1.8, 3.5], method='nearest')
Out[16]:
     x
0.2  0
1.8  2
3.5  4

[3 rows x 1 columns]
```

  This method is also exposed by the lower level `Index.get_indexer` and `Index.get_loc` methods.

- The `read_excel()` function's *sheetname* argument now accepts a list and `None`, to get multiple or all sheets respectively. If more than one sheet is specified, a dictionary is returned. (GH9450)

```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
pd.read_excel('path_to_file.xls', sheetname=['Sheet1', 3])
```

- Allow Stata files to be read incrementally with an iterator; support for long strings in Stata files. See the docs *here* (GH9493:).
- Paths beginning with ~ will now be expanded to begin with the user's home directory (GH9066)
- Added time interval selection in `get_data_yahoo` (GH9071)
- Added `Timestamp.to_datetime64()` to complement `Timedelta.to_timedelta64()` (GH9255)
- `tseries.frequencies.to_offset()` now accepts `Timedelta` as input (GH9064)
- Lag parameter was added to the autocorrelation method of `Series`, defaults to lag-1 autocorrelation (GH9192)
- `Timedelta` will now accept `nanoseconds` keyword in constructor (GH9273)
- SQL code now safely escapes table and column names (GH8986)
- Added auto-complete for `Series.str.<tab>`, `Series.dt.<tab>` and `Series.cat.<tab>` (GH9322)

- `Index.get_indexer` now supports `method='pad'` and `method='backfill'` even for any target array, not just monotonic targets. These methods also work for monotonic decreasing as well as monotonic increasing indexes (GH9258).
- `Index.asof` now works on all index types (GH9258).
- A `verbose` argument has been augmented in `io.read_excel()`, defaults to False. Set to True to print sheet names as they are parsed. (GH9450)
- Added `days_in_month` (compatibility alias `daysinmonth`) property to `Timestamp`, `DatetimeIndex`, `Period`, `PeriodIndex`, and `Series.dt` (GH9572)
- Added `decimal` option in `to_csv` to provide formatting for non-'.' decimal separators (GH781)
- Added `normalize` option for `Timestamp` to normalized to midnight (GH8794)
- Added example for `DataFrame` import to R using HDF5 file and `rhdf5` library. See the *documentation* for more (GH9636).

Backwards incompatible API changes

Changes in timedelta

In v0.15.0 a new scalar type `Timedelta` was introduced, that is a sub-class of `datetime.timedelta`. Mentioned *here* was a notice of an API change w.r.t. the `.seconds` accessor. The intent was to provide a user-friendly set of accessors that give the 'natural' value for that unit, e.g. if you had a `Timedelta('1 day, 10:11:12')`, then `.seconds` would return 12. However, this is at odds with the definition of `datetime.timedelta`, which defines `.seconds` as `10 * 3600 + 11 * 60 + 12 == 36672`.

So in v0.16.0, we are restoring the API to match that of `datetime.timedelta`. Further, the component values are still available through the `.components` accessor. This affects the `.seconds` and `.microseconds` accessors, and removes the `.hours`, `.minutes`, `.milliseconds` accessors. These changes affect `TimedeltaIndex` and the Series `.dt` accessor as well. (GH9185, GH9139)

Previous behavior

```
In [2]: t = pd.Timedelta('1 day, 10:11:12.100123')

In [3]: t.days
Out[3]: 1

In [4]: t.seconds
Out[4]: 12

In [5]: t.microseconds
Out[5]: 123
```

New behavior

```
In [17]: t = pd.Timedelta('1 day, 10:11:12.100123')

In [18]: t.days
Out[18]: 1

In [19]: t.seconds
Out[19]: 36672

In [20]: t.microseconds
Out[20]: 100123
```

Using `.components` allows the full component access

```
In [21]: t.components
Out[21]: Components(days=1, hours=10, minutes=11, seconds=12, milliseconds=100,␣
↪microseconds=123, nanoseconds=0)

In [22]: t.components.seconds
Out[22]: 12
```

Indexing changes

The behavior of a small sub-set of edge cases for using `.loc` have changed (GH8613). Furthermore we have improved the content of the error messages that are raised:

- Slicing with `.loc` where the start and/or stop bound is not found in the index is now allowed; this previously would raise a `KeyError`. This makes the behavior the same as `.ix` in this case. This change is only for slicing, not when indexing with a single label.

```
In [23]: df = pd.DataFrame(np.random.randn(5, 4),
   ....:                   columns=list('ABCD'),
   ....:                   index=pd.date_range('20130101', periods=5))
   ....:

In [24]: df
Out[24]:
                   A         B         C         D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401

[5 rows x 4 columns]

In [25]: s = pd.Series(range(5), [-2, -1, 1, 2, 3])

In [26]: s
Out[26]:
-2    0
-1    1
 1    2
 2    3
 3    4
Length: 5, dtype: int64
```

Previous behavior

```
In [4]: df.loc['2013-01-02':'2013-01-10']
KeyError: 'stop bound [2013-01-10] is not in the [index]'

In [6]: s.loc[-10:3]
KeyError: 'start bound [-10] is not the [index]'
```

New behavior

```
In [27]: df.loc['2013-01-02':'2013-01-10']
Out[27]:
                   A         B         C         D
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401

[4 rows x 4 columns]

In [28]: s.loc[-10:3]
Out[28]:
-2    0
-1    1
 1    2
 2    3
 3    4
Length: 5, dtype: int64
```

- Allow slicing with float-like values on an integer index for `.ix`. Previously this was only enabled for `.loc`:

  Previous behavior

```
In [8]: s.ix[-1.0:2]
TypeError: the slice start value [-1.0] is not a proper indexer for this index␣
↪type (Int64Index)
```

  New behavior

```
In [2]: s.ix[-1.0:2]
Out[2]:
-1    1
 1    2
 2    3
dtype: int64
```

- Provide a useful exception for indexing with an invalid type for that index when using `.loc`. For example trying to use `.loc` on an index of type `DatetimeIndex` or `PeriodIndex` or `TimedeltaIndex`, with an integer (or a float).

  Previous behavior

```
In [4]: df.loc[2:3]
KeyError: 'start bound [2] is not the [index]'
```

  New behavior

```
In [4]: df.loc[2:3]
TypeError: Cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex
↪'> with <type 'int'> keys
```

Categorical changes

In prior versions, `Categoricals` that had an unspecified ordering (meaning no `ordered` keyword was passed) were defaulted as `ordered` Categoricals. Going forward, the `ordered` keyword in the `Categorical` constructor will default to `False`. Ordering must now be explicit.

Furthermore, previously you *could* change the `ordered` attribute of a Categorical by just setting the attribute, e.g. `cat.ordered=True`; This is now deprecated and you should use `cat.as_ordered()` or `cat.as_unordered()`. These will by default return a **new** object and not modify the existing object. (GH9347, GH9190)

Previous behavior

```
In [3]: s = pd.Series([0, 1, 2], dtype='category')

In [4]: s
Out[4]:
0    0
1    1
2    2
dtype: category
Categories (3, int64): [0 < 1 < 2]

In [5]: s.cat.ordered
Out[5]: True

In [6]: s.cat.ordered = False

In [7]: s
Out[7]:
0    0
1    1
2    2
dtype: category
Categories (3, int64): [0, 1, 2]
```

New behavior

```
In [29]: s = pd.Series([0, 1, 2], dtype='category')

In [30]: s
Out[30]:
0    0
1    1
2    2
Length: 3, dtype: category
Categories (3, int64): [0, 1, 2]

In [31]: s.cat.ordered
Out[31]: False

In [32]: s = s.cat.as_ordered()

In [33]: s
Out[33]:
0    0
1    1
2    2
```

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```
Length: 3, dtype: category
Categories (3, int64): [0 < 1 < 2]

In [34]: s.cat.ordered
Out[34]: True

# you can set in the constructor of the Categorical
In [35]: s = pd.Series(pd.Categorical([0, 1, 2], ordered=True))

In [36]: s
Out[36]:
0    0
1    1
2    2
Length: 3, dtype: category
Categories (3, int64): [0 < 1 < 2]

In [37]: s.cat.ordered
Out[37]: True
```

For ease of creation of series of categorical data, we have added the ability to pass keywords when calling `.astype()`. These are passed directly to the constructor.

```
In [54]: s = pd.Series(["a", "b", "c", "a"]).astype('category', ordered=True)

In [55]: s
Out[55]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a < b < c]

In [56]: s = (pd.Series(["a", "b", "c", "a"])
   ....:         .astype('category', categories=list('abcdef'), ordered=False))

In [57]: s
Out[57]:
0    a
1    b
2    c
3    a
dtype: category
Categories (6, object): [a, b, c, d, e, f]
```

Other API changes

- `Index.duplicated` now returns `np.array(dtype=bool)` rather than `Index(dtype=object)` containing `bool` values. (GH8875)
- `DataFrame.to_json` now returns accurate type serialisation for each column for frames of mixed dtype (GH9037)

  Previously data was coerced to a common dtype before serialisation, which for example resulted in integers being serialised to floats:

```
In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1.0,"1":2.0}}'
```

  Now each column is serialised using its correct dtype:

```
In [2]:  pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1,"1":2}}'
```

- `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex.summary` now output the same format. (GH9116)
- `TimedeltaIndex.freqstr` now output the same string format as `DatetimeIndex`. (GH9116)
- Bar and horizontal bar plots no longer add a dashed line along the info axis. The prior style can be achieved with matplotlib's `axhline` or `axvline` methods (GH9088).
- `Series` accessors `.dt`, `.cat` and `.str` now raise `AttributeError` instead of `TypeError` if the series does not contain the appropriate type of data (GH9617). This follows Python's built-in exception hierarchy more closely and ensures that tests like `hasattr(s, 'cat')` are consistent on both Python 2 and 3.
- `Series` now supports bitwise operation for integral types (GH9016). Previously even if the input dtypes were integral, the output dtype was coerced to `bool`.

  Previous behavior

```
In [2]: pd.Series([0, 1, 2, 3], list('abcd')) | pd.Series([4, 4, 4, 4], list('abcd
↪'))
Out[2]:
a    True
b    True
c    True
d    True
dtype: bool
```

  New behavior. If the input dtypes are integral, the output dtype is also integral and the output values are the result of the bitwise operation.

```
In [2]: pd.Series([0, 1, 2, 3], list('abcd')) | pd.Series([4, 4, 4, 4], list('abcd
↪'))
Out[2]:
a    4
b    5
c    6
d    7
dtype: int64
```

- During division involving a `Series` or `DataFrame`, `0/0` and `0//0` now give `np.nan` instead of `np.inf`. (GH9144, GH8445)

Previous behavior

```
In [2]: p = pd.Series([0, 1])

In [3]: p / 0
Out[3]:
0    inf
1    inf
dtype: float64

In [4]: p // 0
Out[4]:
0    inf
1    inf
dtype: float64
```

New behavior

```
In [38]: p = pd.Series([0, 1])

In [39]: p / 0
Out[39]:
0    NaN
1    inf
Length: 2, dtype: float64

In [40]: p // 0
Out[40]:
0    NaN
1    inf
Length: 2, dtype: float64
```

- `Series.values_counts` and `Series.describe` for categorical data will now put `NaN` entries at the end. (GH9443)
- `Series.describe` for categorical data will now give counts and frequencies of 0, not `NaN`, for unused categories (GH9443)
- Due to a bug fix, looking up a partial string label with `DatetimeIndex.asof` now includes values that match the string, even if they are after the start of the partial string label (GH9258).

  Old behavior:

```
In [4]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[4]: Timestamp('2000-01-31 00:00:00')
```

  Fixed behavior:

```
In [41]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[41]: Timestamp('2000-02-28 00:00:00')
```

  To reproduce the old behavior, simply add more precision to the label (e.g., use `2000-02-01` instead of `2000-02`).

Deprecations

- The `rplot` trellis plotting interface is deprecated and will be removed in a future version. We refer to external packages like seaborn for similar but more refined functionality (GH3445). The documentation includes some examples how to convert your existing code from `rplot` to seaborn here.
- The `pandas.sandbox.qtpandas` interface is deprecated and will be removed in a future version. We refer users to the external package pandas-qt. (GH9615)
- The `pandas.rpy` interface is deprecated and will be removed in a future version. Similar functionality can be accessed through the rpy2 project (GH9602)
- Adding `DatetimeIndex/PeriodIndex` to another `DatetimeIndex/PeriodIndex` is being deprecated as a set-operation. This will be changed to a `TypeError` in a future version. `.union()` should be used for the union set operation. (GH9094)
- Subtracting `DatetimeIndex/PeriodIndex` from another `DatetimeIndex/PeriodIndex` is being deprecated as a set-operation. This will be changed to an actual numeric subtraction yielding a `TimeDeltaIndex` in a future version. `.difference()` should be used for the differencing set operation. (GH9094)

Removal of prior version deprecations/changes

- `DataFrame.pivot_table` and `crosstab`'s `rows` and `cols` keyword arguments were removed in favor of `index` and `columns` (GH6581)
- `DataFrame.to_excel` and `DataFrame.to_csv` `cols` keyword argument was removed in favor of `columns` (GH6581)
- Removed `convert_dummies` in favor of `get_dummies` (GH6581)
- Removed `value_range` in favor of `describe` (GH6581)

Performance improvements

- Fixed a performance regression for `.loc` indexing with an array or list-like (GH9126:).
- `DataFrame.to_json` 30x performance improvement for mixed dtype frames. (GH9037)
- Performance improvements in `MultiIndex.duplicated` by working with labels instead of values (GH9125)
- Improved the speed of `nunique` by calling `unique` instead of `value_counts` (GH9129, GH7771)
- Performance improvement of up to 10x in `DataFrame.count` and `DataFrame.dropna` by taking advantage of homogeneous/heterogeneous dtypes appropriately (GH9136)
- Performance improvement of up to 20x in `DataFrame.count` when using a `MultiIndex` and the `level` keyword argument (GH9163)
- Performance and memory usage improvements in `merge` when key space exceeds `int64` bounds (GH9151)
- Performance improvements in multi-key `groupby` (GH9429)
- Performance improvements in `MultiIndex.sortlevel` (GH9445)
- Performance and memory usage improvements in `DataFrame.duplicated` (GH9398)
- Cythonized `Period` (GH9440)
- Decreased memory usage on `to_hdf` (GH9648)

Bug fixes

- Changed `.to_html` to remove leading/trailing spaces in table body (GH4987)
- Fixed issue using `read_csv` on s3 with Python 3 (GH9452)
- Fixed compatibility issue in `DatetimeIndex` affecting architectures where `numpy.int_` defaults to `numpy.int32` (GH8943)
- Bug in Panel indexing with an object-like (GH9140)
- Bug in the returned `Series.dt.components` index was reset to the default index (GH9247)
- Bug in `Categorical.__getitem__/__setitem__` with listlike input getting incorrect results from indexer coercion (GH9469)
- Bug in partial setting with a DatetimeIndex (GH9478)
- Bug in groupby for integer and datetime64 columns when applying an aggregator that caused the value to be changed when the number was sufficiently large (GH9311, GH6620)
- Fixed bug in `to_sql` when mapping a `Timestamp` object column (datetime column with timezone info) to the appropriate sqlalchemy type (GH9085).
- Fixed bug in `to_sql` `dtype` argument not accepting an instantiated SQLAlchemy type (GH9083).
- Bug in `.loc` partial setting with a `np.datetime64` (GH9516)
- Incorrect dtypes inferred on datetimelike looking `Series` & on `.xs` slices (GH9477)
- Items in `Categorical.unique()` (and `s.unique()` if `s` is of dtype `category`) now appear in the order in which they are originally found, not in sorted order (GH9331). This is now consistent with the behavior for other dtypes in pandas.
- Fixed bug on big endian platforms which produced incorrect results in `StataReader` (GH8688).
- Bug in `MultiIndex.has_duplicates` when having many levels causes an indexer overflow (GH9075, GH5873)
- Bug in `pivot` and `unstack` where `nan` values would break index alignment (GH4862, GH7401, GH7403, GH7405, GH7466, GH9497)
- Bug in left `join` on MultiIndex with `sort=True` or null values (GH9210).
- Bug in `MultiIndex` where inserting new keys would fail (GH9250).
- Bug in `groupby` when key space exceeds `int64` bounds (GH9096).
- Bug in `unstack` with `TimedeltaIndex` or `DatetimeIndex` and nulls (GH9491).
- Bug in `rank` where comparing floats with tolerance will cause inconsistent behaviour (GH8365).
- Fixed character encoding bug in `read_stata` and `StataReader` when loading data from a URL (GH9231).
- Bug in adding `offsets.Nano` to other offsets raises `TypeError` (GH9284)
- Bug in `DatetimeIndex` iteration, related to (GH8890), fixed in (GH9100)
- Bugs in `resample` around DST transitions. This required fixing offset classes so they behave correctly on DST transitions. (GH5172, GH8744, GH8653, GH9173, GH9468).
- Bug in binary operator method (eg `.mul()`) alignment with integer levels (GH9463).
- Bug in boxplot, scatter and hexbin plot may show an unnecessary warning (GH8877)
- Bug in subplot with `layout` kw may show unnecessary warning (GH9464)

- Bug in using grouper functions that need passed through arguments (e.g. axis), when using wrapped function (e.g. `fillna`), (GH9221)
- `DataFrame` now properly supports simultaneous `copy` and `dtype` arguments in constructor (GH9099)
- Bug in `read_csv` when using skiprows on a file with CR line endings with the c engine. (GH9079)
- `isnull` now detects `NaT` in `PeriodIndex` (GH9129)
- Bug in groupby `.nth()` with a multiple column groupby (GH8979)
- Bug in `DataFrame.where` and `Series.where` coerce numerics to string incorrectly (GH9280)
- Bug in `DataFrame.where` and `Series.where` raise `ValueError` when string list-like is passed. (GH9280)
- Accessing `Series.str` methods on with non-string values now raises `TypeError` instead of producing incorrect results (GH9184)
- Bug in `DatetimeIndex.__contains__` when index has duplicates and is not monotonic increasing (GH9512)
- Fixed division by zero error for `Series.kurt()` when all values are equal (GH9197)
- Fixed issue in the `xlsxwriter` engine where it added a default 'General' format to cells if no other format was applied. This prevented other row or column formatting being applied. (GH9167)
- Fixes issue with `index_col=False` when `usecols` is also specified in `read_csv`. (GH9082)
- Bug where `wide_to_long` would modify the input stub names list (GH9204)
- Bug in `to_sql` not storing float64 values using double precision. (GH9009)
- `SparseSeries` and `SparsePanel` now accept zero argument constructors (same as their non-sparse counterparts) (GH9272).
- Regression in merging `Categorical` and `object` dtypes (GH9426)
- Bug in `read_csv` with buffer overflows with certain malformed input files (GH9205)
- Bug in groupby MultiIndex with missing pair (GH9049, GH9344)
- Fixed bug in `Series.groupby` where grouping on `MultiIndex` levels would ignore the sort argument (GH9444)
- Fix bug in `DataFrame.Groupby` where `sort=False` is ignored in the case of Categorical columns. (GH8868)
- Fixed bug with reading CSV files from Amazon S3 on python 3 raising a TypeError (GH9452)
- Bug in the Google BigQuery reader where the 'jobComplete' key may be present but False in the query results (GH8728)
- Bug in `Series.values_counts` with excluding `NaN` for categorical type `Series` with `dropna=True` (GH9443)
- Fixed missing numeric_only option for `DataFrame.std/var/sem` (GH9201)
- Support constructing `Panel` or `Panel4D` with scalar data (GH8285)
- `Series` text representation disconnected from `max_rows`/`max_columns` (GH7508).
- `Series` number formatting inconsistent when truncated (GH8532).

  Previous behavior

```
In [2]: pd.options.display.max_rows = 10
In [3]: s = pd.Series([1,1,1,1,1,1,1,1,1,0.9999,1,1]*10)
In [4]: s
Out[4]:
0    1
1    1
2    1
...
127    0.9999
128    1.0000
129    1.0000
Length: 130, dtype: float64
```

New behavior

```
0      1.0000
1      1.0000
2      1.0000
3      1.0000
4      1.0000
...
125    1.0000
126    1.0000
127    0.9999
128    1.0000
129    1.0000
dtype: float64
```

- A Spurious `SettingWithCopy` Warning was generated when setting a new item in a frame in some cases (GH8730)

  The following would previously report a `SettingWithCopy` Warning.

```
In [42]: df1 = pd.DataFrame({'x': pd.Series(['a', 'b', 'c']),
   ....:                     'y': pd.Series(['d', 'e', 'f'])})
   ....:

In [43]: df2 = df1[['x']]

In [44]: df2['y'] = ['g', 'h', 'i']
```

Contributors

A total of 60 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Aaron Toth +
- Alan Du +
- Alessandro Amici +
- Artemy Kolchinsky
- Ashwini Chaudhary +
- Ben Schiller
- Bill Letson

- Brandon Bradley +
- Chau Hoang +
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- David Cottrell +
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- unutbu

5.14 Version 0.15

5.14.1 Version 0.15.2 (December 12, 2014)

This is a minor release from 0.15.1 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. A small number of API changes were necessary to fix existing bugs. We recommend that all users upgrade to this version.

- *Enhancements*
- *API Changes*
- *Performance Improvements*
- *Bug Fixes*

API changes

- Indexing in `MultiIndex` beyond lex-sort depth is now supported, though a lexically sorted index will have a better performance. (GH2646)

```
In [1]: df = pd.DataFrame({'jim':[0, 0, 1, 1],
   ...:                    'joe':['x', 'x', 'z', 'y'],
   ...:                    'jolie':np.random.rand(4)}).set_index(['jim', 'joe'])
   ...:

In [2]: df
```

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```
Out[2]:
             jolie
jim joe
0   x    0.126970
    x    0.966718
1   z    0.260476
    y    0.897237

[4 rows x 1 columns]

In [3]: df.index.lexsort_depth
Out[3]: 1

# in prior versions this would raise a KeyError
# will now show a PerformanceWarning
In [4]: df.loc[(1, 'z')]
Out[4]:
             jolie
jim joe
1   z    0.260476

[1 rows x 1 columns]

# lexically sorting
In [5]: df2 = df.sort_index()

In [6]: df2
Out[6]:
             jolie
jim joe
0   x    0.126970
    x    0.966718
1   y    0.897237
    z    0.260476

[4 rows x 1 columns]

In [7]: df2.index.lexsort_depth
Out[7]: 2

In [8]: df2.loc[(1,'z')]
Out[8]:
             jolie
jim joe
1   z    0.260476

[1 rows x 1 columns]
```

- Bug in unique of Series with `category` dtype, which returned all categories regardless whether they were "used" or not (see GH8559 for the discussion). Previous behaviour was to return all categories:

```
In [3]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [4]: cat
Out[4]:
[a, b, a]
```

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```
Categories (3, object): [a < b < c]

In [5]: cat.unique()
Out[5]: array(['a', 'b', 'c'], dtype=object)
```

Now, only the categories that do effectively occur in the array are returned:

```
In [9]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [10]: cat.unique()
Out[10]:
['a', 'b']
Categories (2, object): ['a', 'b']
```

- `Series.all` and `Series.any` now support the `level` and `skipna` parameters. `Series.all`, `Series.any`, `Index.all`, and `Index.any` no longer support the `out` and `keepdims` parameters, which existed for compatibility with ndarray. Various index types no longer support the `all` and `any` aggregation functions and will now raise `TypeError`. (GH8302).
- Allow equality comparisons of Series with a categorical dtype and object dtype; previously these would raise `TypeError` (GH8938)
- Bug in `NDFrame`: conflicting attribute/column names now behave consistently between getting and setting. Previously, when both a column and attribute named `y` existed, `data.y` would return the attribute, while `data.y = z` would update the column (GH8994)

```
In [11]: data = pd.DataFrame({'x': [1, 2, 3]})

In [12]: data.y = 2

In [13]: data['y'] = [2, 4, 6]

In [14]: data
Out[14]:
   x  y
0  1  2
1  2  4
2  3  6

[3 rows x 2 columns]

# this assignment was inconsistent
In [15]: data.y = 5
```

Old behavior:

```
In [6]: data.y
Out[6]: 2

In [7]: data['y'].values
Out[7]: array([5, 5, 5])
```

New behavior:

```
In [16]: data.y
Out[16]: 5
```

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```
In [17]: data['y'].values
Out[17]: array([2, 4, 6])
```

- `Timestamp('now')` is now equivalent to `Timestamp.now()` in that it returns the local time rather than UTC. Also, `Timestamp('today')` is now equivalent to `Timestamp.today()` and both have `tz` as a possible argument. (GH9000)
- Fix negative step support for label-based slices (GH8753)

  Old behavior:

```
In [1]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])
Out[1]:
a    0
b    1
c    2
dtype: int64

In [2]: s.loc['c':'a':-1]
Out[2]:
c    2
dtype: int64
```

  New behavior:

```
In [18]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])

In [19]: s.loc['c':'a':-1]
Out[19]:
c    2
b    1
a    0
Length: 3, dtype: int64
```

Enhancements

`Categorical` enhancements:

- Added ability to export Categorical data to Stata (GH8633). See *here* for limitations of categorical variables exported to Stata data files.
- Added flag `order_categoricals` to `StataReader` and `read_stata` to select whether to order imported categorical data (GH8836). See *here* for more information on importing categorical variables from Stata data files.
- Added ability to export Categorical data to/from HDF5 (GH7621). Queries work the same as if it was an object array. However, the `category` dtyped data is stored in a more efficient manner. See *here* for an example and caveats w.r.t. prior versions of pandas.
- Added support for `searchsorted()` on `Categorical` class (GH8420).

Other enhancements:

- Added the ability to specify the SQL type of columns when writing a DataFrame to a database (GH8778). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```
from sqlalchemy.types import String
data.to_sql('data_dtype', engine, dtype={'Col_1': String})  # noqa F821
```

- `Series.all` and `Series.any` now support the `level` and `skipna` parameters (GH8302):

```
In [20]: s = pd.Series([False, True, False], index=[0, 0, 1])

In [21]: s.any(level=0)
Out[21]:
0     True
1    False
Length: 2, dtype: bool
```

- `Panel` now supports the `all` and `any` aggregation functions. (GH8302):

```
>>> p = pd.Panel(np.random.rand(2, 5, 4) > 0.1)
>>> p.all()
       0      1      2     3
0   True   True   True  True
1   True  False   True  True
2   True   True   True  True
3  False   True  False  True
4   True   True   True  True
```

- Added support for `utcfromtimestamp()`, `fromtimestamp()`, and `combine()` on `Timestamp` class (GH5351).
- Added Google Analytics (*pandas.io.ga*) basic documentation (GH8835). See here.
- `Timedelta` arithmetic returns `NotImplemented` in unknown cases, allowing extensions by custom classes (GH8813).
- `Timedelta` now supports arithmetic with `numpy.ndarray` objects of the appropriate dtype (numpy 1.8 or newer only) (GH8884).
- Added `Timedelta.to_timedelta64()` method to the public API (GH8884).
- Added `gbq.generate_bq_schema()` function to the gbq module (GH8325).
- `Series` now works with map objects the same way as generators (GH8909).
- Added context manager to `HDFStore` for automatic closing (GH8791).
- `to_datetime` gains an `exact` keyword to allow for a format to not require an exact match for a provided format string (if its `False`). `exact` defaults to `True` (meaning that exact matching is still the default) (GH8904)
- Added `axvlines` boolean option to parallel_coordinates plot function, determines whether vertical lines will be printed, default is True
- Added ability to read table footers to read_html (GH8552)
- `to_sql` now infers data types of non-NA values for columns that contain NA values and have dtype `object` (GH8778).

Performance

- Reduce memory usage when skiprows is an integer in read_csv (GH8681)
- Performance boost for `to_datetime` conversions with a passed `format=`, and the `exact=False` (GH8904)

Bug fixes

- Bug in concat of Series with `category` dtype which were coercing to `object`. (GH8641)
- Bug in Timestamp-Timestamp not returning a Timedelta type and datelike-datelike ops with timezones (GH8865)
- Made consistent a timezone mismatch exception (either tz operated with None or incompatible timezone), will now return `TypeError` rather than `ValueError` (a couple of edge cases only), (GH8865)
- Bug in using a `pd.Grouper(key=...)` with no level/axis or level only (GH8795, GH8866)
- Report a `TypeError` when invalid/no parameters are passed in a groupby (GH8015)
- Bug in packaging pandas with `py2app/cx_Freeze` (GH8602, GH8831)
- Bug in `groupby` signatures that didn't include *args or **kwargs (GH8733).
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Unclear error message in csv parsing when passing dtype and names and the parsed data is a different data type (GH8833)
- Bug in slicing a MultiIndex with an empty list and at least one boolean indexer (GH8781)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo (GH8761).
- `Timedelta` kwargs may now be numpy ints and floats (GH8757).
- Fixed several outstanding bugs for `Timedelta` arithmetic and comparisons (GH8813, GH5963, GH5436).
- `sql_schema` now generates dialect appropriate `CREATE TABLE` statements (GH8697)
- `slice` string method now takes step into account (GH8754)
- Bug in `BlockManager` where setting values with different type would break block integrity (GH8850)
- Bug in `DatetimeIndex` when using `time` object as key (GH8667)
- Bug in `merge` where `how='left'` and `sort=False` would not preserve left frame order (GH7331)
- Bug in `MultiIndex.reindex` where reindexing at level would not reorder labels (GH4088)
- Bug in certain operations with dateutil timezones, manifesting with dateutil 2.3 (GH8639)
- Regression in DatetimeIndex iteration with a Fixed/Local offset timezone (GH8890)
- Bug in `to_datetime` when parsing a nanoseconds using the `%f` format (GH8989)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Fix: The font size was only set on x axis if vertical or the y axis if horizontal. (GH8765)
- Fixed division by 0 when reading big csv files in python 3 (GH8621)
- Bug in outputting a MultiIndex with `to_html,index=False` which would add an extra column (GH8452)

- Imported categorical variables from Stata files retain the ordinal information in the underlying data (GH8836).
- Defined `.size` attribute across `NDFrame` objects to provide compat with numpy >= 1.9.1; buggy with `np.array_split` (GH8846)
- Skip testing of histogram plots for matplotlib <= 1.2 (GH8648).
- Bug where `get_data_google` returned object dtypes (GH3995)
- Bug in `DataFrame.stack(..., dropna=False)` when the DataFrame's `columns` is a `MultiIndex` whose `labels` do not reference all its `levels`. (GH8844)
- Bug in that Option context applied on `__enter__` (GH8514)
- Bug in resample that causes a ValueError when resampling across multiple days and the last offset is not calculated from the start of the range (GH8683)
- Bug where `DataFrame.plot(kind='scatter')` fails when checking if an np.array is in the DataFrame (GH8852)
- Bug in `pd.infer_freq/DataFrame.inferred_freq` that prevented proper sub-daily frequency inference when the index contained DST days (GH8772).
- Bug where index name was still used when plotting a series with `use_index=False` (GH8558).
- Bugs when trying to stack multiple columns, when some (or all) of the level names are numbers (GH8584).
- Bug in `MultiIndex` where `__contains__` returns wrong result if index is not lexically sorted or unique (GH7724)
- BUG CSV: fix problem with trailing white space in skipped rows, (GH8679), (GH8661), (GH8983)
- Regression in `Timestamp` does not parse 'Z' zone designator for UTC (GH8771)
- Bug in `StataWriter` the produces writes strings with 244 characters irrespective of actual size (GH8969)
- Fixed ValueError raised by cummin/cummax when datetime64 Series contains NaT. (GH8965)
- Bug in DataReader returns object dtype if there are missing values (GH8980)
- Bug in plotting if sharex was enabled and index was a timeseries, would show labels on multiple axes (GH3964).
- Bug where passing a unit to the TimedeltaIndex constructor applied the to nano-second conversion twice. (GH9011).
- Bug in plotting of a period-like array (GH9012)

Contributors

A total of 49 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.14.2 Version 0.15.1 (November 9, 2014)

This is a minor bug-fix release from 0.15.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- *Enhancements*
- *API Changes*
- *Bug Fixes*

API changes

- `s.dt.hour` and other `.dt` accessors will now return `np.nan` for missing values (rather than previously -1), (GH8689)

```
In [1]: s = pd.Series(pd.date_range("20130101", periods=5, freq="D"))

In [2]: s.iloc[2] = np.nan

In [3]: s
Out[3]:
0   2013-01-01
1   2013-01-02
2          NaT
3   2013-01-04
4   2013-01-05
Length: 5, dtype: datetime64[ns]
```

previous behavior:

```
In [6]: s.dt.hour
Out[6]:
0    0
1    0
2   -1
3    0
4    0
dtype: int64
```

current behavior:

```
In [4]: s.dt.hour
Out[4]:
0    0.0
1    0.0
2    NaN
```

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```
3    0.0
4    0.0
Length: 5, dtype: float64
```

- `groupby` with `as_index=False` will not add erroneous extra columns to result (GH8582):

```
In [5]: np.random.seed(2718281)

In [6]: df = pd.DataFrame(np.random.randint(0, 100, (10, 2)), columns=["jim", "joe
↪"])

In [7]: df.head()
Out[7]:
   jim  joe
0   61   81
1   96   49
2   55   65
3   72   51
4   77   12

[5 rows x 2 columns]

In [8]: ts = pd.Series(5 * np.random.randint(0, 3, 10))
```

previous behavior:

```
In [4]: df.groupby(ts, as_index=False).max()
Out[4]:
   NaN  jim  joe
0    0   72   83
1    5   77   84
2   10   96   65
```

current behavior:

```
In [9]: df.groupby(ts, as_index=False).max()
Out[9]:
   jim  joe
0   72   83
1   77   84
2   96   65

[3 rows x 2 columns]
```

- `groupby` will not erroneously exclude columns if the column name conflicts with the grouper name (GH8112):

```
In [10]: df = pd.DataFrame({"jim": range(5), "joe": range(5, 10)})

In [11]: df
Out[11]:
   jim  joe
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
```

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```
[5 rows x 2 columns]

In [12]: gr = df.groupby(df["jim"] < 2)
```

previous behavior (excludes 1st column from output):

```
In [4]: gr.apply(sum)
Out[4]:
       joe
jim
False   24
True    11
```

current behavior:

```
In [13]: gr.apply(sum)
Out[13]:
       jim  joe
jim
False    9   24
True     1   11

[2 rows x 2 columns]
```

- Support for slicing with monotonic decreasing indexes, even if `start` or `stop` is not found in the index (GH7860):

```
In [14]: s = pd.Series(["a", "b", "c", "d"], [4, 3, 2, 1])

In [15]: s
Out[15]:
4    a
3    b
2    c
1    d
Length: 4, dtype: object
```

previous behavior:

```
In [8]: s.loc[3.5:1.5]
KeyError: 3.5
```

current behavior:

```
In [16]: s.loc[3.5:1.5]
Out[16]:
3    b
2    c
Length: 2, dtype: object
```

- `io.data.Options` has been fixed for a change in the format of the Yahoo Options page (GH8612), (GH8741)

Note: As a result of a change in Yahoo's option page layout, when an expiry date is given, `Options` methods

now return data for a single expiry date. Previously, methods returned all data for the selected month.

The `month` and `year` parameters have been undeprecated and can be used to get all options data for a given month.

If an expiry date that is not valid is given, data for the next expiry after the given date is returned.

Option data frames are now saved on the instance as `callsYYMMDD` or `putsYYMMDD`. Previously they were saved as `callsMMYY` and `putsMMYY`. The next expiry is saved as `calls` and `puts`.

New features:

- The expiry parameter can now be a single date or a list-like object containing dates.
- A new property `expiry_dates` was added, which returns all available expiry dates.

Current behavior:

```
In [17]: from pandas.io.data import Options

In [18]: aapl = Options('aapl', 'yahoo')

In [19]: aapl.get_call_data().iloc[0:5, 0:1]
Out[19]:
                                                 Last
Strike Expiry     Type Symbol
80     2014-11-14 call AAPL141114C00080000  29.05
84     2014-11-14 call AAPL141114C00084000  24.80
85     2014-11-14 call AAPL141114C00085000  24.05
86     2014-11-14 call AAPL141114C00086000  22.76
87     2014-11-14 call AAPL141114C00087000  21.74

In [20]: aapl.expiry_dates
Out[20]:
[datetime.date(2014, 11, 14),
 datetime.date(2014, 11, 22),
 datetime.date(2014, 11, 28),
 datetime.date(2014, 12, 5),
 datetime.date(2014, 12, 12),
 datetime.date(2014, 12, 20),
 datetime.date(2015, 1, 17),
 datetime.date(2015, 2, 20),
 datetime.date(2015, 4, 17),
 datetime.date(2015, 7, 17),
 datetime.date(2016, 1, 15),
 datetime.date(2017, 1, 20)]

In [21]: aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3]).iloc[0:5, 0:1]
Out[21]:
                                               Last
Strike Expiry     Type Symbol
109    2014-11-22 call AAPL141122C00109000  1.48
       2014-11-28 call AAPL141128C00109000  1.79
110    2014-11-14 call AAPL141114C00110000  0.55
       2014-11-22 call AAPL141122C00110000  1.02
       2014-11-28 call AAPL141128C00110000  1.32
```

- pandas now also registers the `datetime64` dtype in matplotlib's units registry to plot such values as datetimes. This is activated once pandas is imported. In previous versions, plotting an array of `datetime64` values will

have resulted in plotted integer values. To keep the previous behaviour, you can do `del matplotlib.units.registry[np.datetime64]` (GH8614).

Enhancements

- `concat` permits a wider variety of iterables of pandas objects to be passed as the first parameter (GH8645):

```
In [17]: from collections import deque

In [18]: df1 = pd.DataFrame([1, 2, 3])

In [19]: df2 = pd.DataFrame([4, 5, 6])
```

previous behavior:

```
In [7]: pd.concat(deque((df1, df2)))
TypeError: first argument must be a list-like of pandas objects, you passed an␣
↪object of type "deque"
```

current behavior:

```
In [20]: pd.concat(deque((df1, df2)))
Out[20]:
   0
0  1
1  2
2  3
0  4
1  5
2  6

[6 rows x 1 columns]
```

- Represent `MultiIndex` labels with a dtype that utilizes memory based on the level size. In prior versions, the memory usage was a constant 8 bytes per element in each level. In addition, in prior versions, the *reported* memory usage was incorrect as it didn't show the usage for the memory occupied by the underling data array. (GH8456)

```
In [21]: dfi = pd.DataFrame(
   ....:     1, index=pd.MultiIndex.from_product([["a"], range(1000)]), columns=[
↪"A"]
   ....: )
   ....:
```

previous behavior:

```
# this was underreported in prior versions
In [1]: dfi.memory_usage(index=True)
Out[1]:
Index    8000 # took about 24008 bytes in < 0.15.1
A        8000
dtype: int64
```

current behavior:

```
In [22]: dfi.memory_usage(index=True)
Out[22]:
Index    44212
A         8000
Length: 2, dtype: int64
```

- Added Index properties `is_monotonic_increasing` and `is_monotonic_decreasing` (GH8680).
- Added option to select columns when importing Stata files (GH7935)
- Qualify memory usage in `DataFrame.info()` by adding + if it is a lower bound (GH8578)
- Raise errors in certain aggregation cases where an argument such as `numeric_only` is not handled (GH8592).
- Added support for 3-character ISO and non-standard country codes in `io.wb.download()` (GH8482)
- World Bank data requests now will warn/raise based on an `errors` argument, as well as a list of hard-coded country codes and the World Bank's JSON response. In prior versions, the error messages didn't look at the World Bank's JSON response. Problem-inducing input were simply dropped prior to the request. The issue was that many good countries were cropped in the hard-coded approach. All countries will work now, but some bad countries will raise exceptions because some edge cases break the entire response. (GH8482)
- Added option to `Series.str.split()` to return a `DataFrame` rather than a `Series` (GH8428)
- Added option to `df.info(null_counts=None|True|False)` to override the default display options and force showing of the null-counts (GH8701)

Bug fixes

- Bug in unpickling of a `CustomBusinessDay` object (GH8591)
- Bug in coercing `Categorical` to a records array, e.g. `df.to_records()` (GH8626)
- Bug in `Categorical` not created properly with `Series.to_frame()` (GH8626)
- Bug in coercing in astype of a `Categorical` of a passed `pd.Categorical` (this now raises `TypeError` correctly), (GH8626)
- Bug in `cut`/`qcut` when using `Series` and `retbins=True` (GH8589)
- Bug in writing Categorical columns to an SQL database with `to_sql` (GH8624).
- Bug in comparing `Categorical` of datetime raising when being compared to a scalar datetime (GH8687)
- Bug in selecting from a `Categorical` with `.iloc` (GH8623)
- Bug in groupby-transform with a Categorical (GH8623)
- Bug in duplicated/drop_duplicates with a Categorical (GH8623)
- Bug in `Categorical` reflected comparison operator raising if the first argument was a numpy array scalar (e.g. np.int64) (GH8658)
- Bug in Panel indexing with a list-like (GH8710)
- Compat issue is `DataFrame.dtypes` when `options.mode.use_inf_as_null` is True (GH8722)
- Bug in `read_csv`, `dialect` parameter would not take a string (GH8703)
- Bug in slicing a MultiIndex level with an empty-list (GH8737)
- Bug in numeric index operations of add/sub with Float/Index Index with numpy arrays (GH8608)
- Bug in setitem with empty indexer and unwanted coercion of dtypes (GH8669)

- Bug in ix/loc block splitting on setitem (manifests with integer-like dtypes, e.g. datetime64) (GH8607)
- Bug when doing label based indexing with integers not found in the index for non-unique but monotonic indexes (GH8680).
- Bug when indexing a Float64Index with `np.nan` on numpy 1.7 (GH8980).
- Fix `shape` attribute for `MultiIndex` (GH8609)
- Bug in `GroupBy` where a name conflict between the grouper and columns would break `groupby` operations (GH7115, GH8112)
- Fixed a bug where plotting a column `y` and specifying a label would mutate the index name of the original DataFrame (GH8494)
- Fix regression in plotting of a DatetimeIndex directly with matplotlib (GH8614).
- Bug in `date_range` where partially-specified dates would incorporate current date (GH6961)
- Bug in Setting by indexer to a scalar value with a mixed-dtype `Panel4d` was failing (GH8702)
- Bug where `DataReader`'s would fail if one of the symbols passed was invalid. Now returns data for valid symbols and np.nan for invalid (GH8494)
- Bug in `get_quote_yahoo` that wouldn't allow non-float return values (GH5229).

Contributors

A total of 23 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.14.3 Version 0.15.0 (October 18, 2014)

This is a major release from 0.14.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Warning: pandas >= 0.15.0 will no longer support compatibility with NumPy versions < 1.7.0. If you want to use the latest versions of pandas, please upgrade to NumPy >= 1.7.0 (GH7711)

- Highlights include:
  - The `Categorical` type was integrated as a first-class pandas type, see *here*
  - New scalar type `Timedelta`, and a new index type `TimedeltaIndex`, see *here*
  - New datetimelike properties accessor `.dt` for Series, see *Datetimelike Properties*
  - New DataFrame default display for `df.info()` to include memory usage, see *Memory Usage*
  - `read_csv` will now by default ignore blank lines when parsing, see *here*
  - API change in using Indexes in set operations, see *here*
  - Enhancements in the handling of timezones, see *here*
  - A lot of improvements to the rolling and expanding moment functions, see *here*
  - Internal refactoring of the `Index` class to no longer sub-class `ndarray`, see *Internal Refactoring*
  - dropping support for `PyTables` less than version 3.0.0, and `numexpr` less than version 2.1 (GH7990)
  - Split indexing documentation into *Indexing and Selecting Data* and *MultiIndex / Advanced Indexing*
  - Split out string methods documentation into *Working with Text Data*
- Check the *API Changes* and *deprecations* before updating
- *Other Enhancements*
- *Performance Improvements*
- *Bug Fixes*

Warning: In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (See the *Internal Refactoring*)

Warning: The refactoring in *Categorical* changed the two argument constructor from "codes/labels and levels" to "values and levels (now called 'categories')". This can lead to subtle bugs. If you use *Categorical* directly, please audit your code before updating to this pandas version and change it to use the *from_codes()* constructor. See more on Categorical *here*

New features

Categoricals in Series/DataFrame

Categorical can now be included in Series and DataFrames and gained new methods to manipulate. Thanks to Jan Schulz for much of this API/implementation. (GH3943, GH5313, GH5314, GH7444, GH7839, GH7848, GH7864, GH7914, GH7768, GH8006, GH3678, GH8075, GH8076, GH8143, GH8453, GH8518).

For full docs, see the *categorical introduction* and the *API documentation*.

```
In [1]: df = pd.DataFrame({"id": [1, 2, 3, 4, 5, 6],
   ...:                    "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']})
   ...:

In [2]: df["grade"] = df["raw_grade"].astype("category")

In [3]: df["grade"]
Out[3]:
0    a
1    b
2    b
3    a
4    a
5    e
Name: grade, Length: 6, dtype: category
Categories (3, object): ['a', 'b', 'e']

# Rename the categories
In [4]: df["grade"].cat.categories = ["very good", "good", "very bad"]

# Reorder the categories and simultaneously add the missing categories
In [5]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad",
   ...:                                               "medium", "good", "very good"])
   ...:

In [6]: df["grade"]
Out[6]:
0    very good
1         good
2         good
3    very good
4    very good
5     very bad
Name: grade, Length: 6, dtype: category
Categories (5, object): ['very bad', 'bad', 'medium', 'good', 'very good']

In [7]: df.sort_values("grade")
Out[7]:
   id raw_grade      grade
5   6         e   very bad
```

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```
1   2          b       good
2   3          b       good
0   1          a  very good
3   4          a  very good
4   5          a  very good

[6 rows x 3 columns]

In [8]: df.groupby("grade").size()
Out[8]:
grade
very bad     1
bad          0
medium       0
good         2
very good    3
Length: 5, dtype: int64
```

- `pandas.core.group_agg` and `pandas.core.factor_agg` were removed. As an alternative, construct a dataframe and use `df.groupby(<group>).agg(<func>)`.
- Supplying "codes/labels and levels" to the *`Categorical`* constructor is not supported anymore. Supplying two arguments to the constructor is now interpreted as "values and levels (now called 'categories')". Please change your code to use the *`from_codes()`* constructor.
- The `Categorical.labels` attribute was renamed to `Categorical.codes` and is read only. If you want to manipulate codes, please use one of the *API methods on Categoricals*.
- The `Categorical.levels` attribute is renamed to `Categorical.categories`.

TimedeltaIndex/scalar

We introduce a new scalar type `Timedelta`, which is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes. This type is very similar to how `Timestamp` works for `datetimes`. It is a nice-API box for the type. See the *docs*. (GH3009, GH4533, GH8209, GH8187, GH8190, GH7869, GH7661, GH8345, GH8471)

Warning: `Timedelta` scalars (and `TimedeltaIndex`) component fields are *not the same* as the component fields on a `datetime.timedelta` object. For example, `.seconds` on a `datetime.timedelta` object returns the total number of seconds combined between `hours`, `minutes` and `seconds`. In contrast, the pandas `Timedelta` breaks out hours, minutes, microseconds and nanoseconds separately.

```
# Timedelta accessor
In [9]: tds = pd.Timedelta('31 days 5 min 3 sec')

In [10]: tds.minutes
Out[10]: 5L

In [11]: tds.seconds
Out[11]: 3L

# datetime.timedelta accessor
# this is 5 minutes * 60 + 3 seconds
In [12]: tds.to_pytimedelta().seconds
Out[12]: 303
```

Note: this is no longer true starting from v0.16.0, where full compatibility with `datetime.timedelta` is introduced. See the *0.16.0 whatsnew entry*

Warning: Prior to 0.15.0 `pd.to_timedelta` would return a `Series` for list-like/Series input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for Series input, and `Timedelta` for scalar input.

The arguments to `pd.to_timedelta` are now `(arg,unit='ns',box=True,coerce=False)`, previously were `(arg,box=True,unit='ns')` as these are more logical.

Construct a scalar

```
In [9]: pd.Timedelta('1 days 06:05:01.00003')
Out[9]: Timedelta('1 days 06:05:01.000030')

In [10]: pd.Timedelta('15.5us')
Out[10]: Timedelta('0 days 00:00:00.000015500')

In [11]: pd.Timedelta('1 hour 15.5us')
Out[11]: Timedelta('0 days 01:00:00.000015500')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [12]: pd.Timedelta('-1us')
Out[12]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [13]: pd.Timedelta('nan')
Out[13]: NaT
```

Access fields for a `Timedelta`

```
In [14]: td = pd.Timedelta('1 hour 3m 15.5us')

In [15]: td.seconds
Out[15]: 3780

In [16]: td.microseconds
Out[16]: 15

In [17]: td.nanoseconds
Out[17]: 500
```

Construct a `TimedeltaIndex`

```
In [18]: pd.TimedeltaIndex(['1 days', '1 days, 00:00:05',
   ....:                    np.timedelta64(2, 'D'),
   ....:                    datetime.timedelta(days=2, seconds=2)])
   ....:
Out[18]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00',
                '2 days 00:00:02'],
               dtype='timedelta64[ns]', freq=None)
```

Constructing a `TimedeltaIndex` with a regular range

```
In [19]: pd.timedelta_range('1 days', periods=5, freq='D')
Out[19]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype=
↪'timedelta64[ns]', freq='D')

In [20]: pd.timedelta_range(start='1 days', end='2 days', freq='30T')
Out[20]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
                '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
                '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
                '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
                '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
                '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
                '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
                '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
                '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
                '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
                '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
                '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
                '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
                '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
                '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
                '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
                '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='30T')
```

You can now use a `TimedeltaIndex` as the index of a pandas object

```
In [21]: s = pd.Series(np.arange(5),
   ....:               index=pd.timedelta_range('1 days', periods=5, freq='s'))
   ....:

In [22]: s
Out[22]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
1 days 00:00:03    3
1 days 00:00:04    4
Freq: S, Length: 5, dtype: int64
```

You can select with partial string selections

```
In [23]: s['1 day 00:00:02']
Out[23]: 2

In [24]: s['1 day':'1 day 00:00:02']
Out[24]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
Freq: S, Length: 3, dtype: int64
```

Finally, the combination of `TimedeltaIndex` with `DatetimeIndex` allow certain combination operations that are `NaT` preserving:

```
In [25]: tdi = pd.TimedeltaIndex(['1 days', pd.NaT, '2 days'])
```

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```
In [26]: tdi.tolist()
Out[26]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [27]: dti = pd.date_range('20130101', periods=3)

In [28]: dti.tolist()
Out[28]:
[Timestamp('2013-01-01 00:00:00', freq='D'),
 Timestamp('2013-01-02 00:00:00', freq='D'),
 Timestamp('2013-01-03 00:00:00', freq='D')]

In [29]: (dti + tdi).tolist()
Out[29]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [30]: (dti - tdi).tolist()
Out[30]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

- iteration of a `Series` e.g. `list(Series(...))` of `timedelta64[ns]` would prior to v0.15.0 return `np.timedelta64` for each element. These will now be wrapped in `Timedelta`.

Memory usage

Implemented methods to find memory usage of a DataFrame. See the *FAQ* for more. (GH6852).

A new display option `display.memory_usage` (see *Options and settings*) sets the default behavior of the `memory_usage` argument in the `df.info()` method. By default `display.memory_usage` is `True`.

```
In [31]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
   ....:           'complex128', 'object', 'bool']
   ....:

In [32]: n = 5000

In [33]: data = {t: np.random.randint(100, size=n).astype(t) for t in dtypes}

In [34]: df = pd.DataFrame(data)

In [35]: df['categorical'] = df['object'].astype('category')

In [36]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   int64            5000 non-null   int64
 1   float64          5000 non-null   float64
 2   datetime64[ns]   5000 non-null   datetime64[ns]
 3   timedelta64[ns]  5000 non-null   timedelta64[ns]
 4   complex128       5000 non-null   complex128
 5   object           5000 non-null   object
 6   bool             5000 non-null   bool
 7   categorical      5000 non-null   category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1),␣
↪object(1), timedelta64[ns](1)
memory usage: 288.2+ KB
```

Additionally *memory_usage()* is an available method for a dataframe object which returns the memory usage of each column.

```
In [37]: df.memory_usage(index=True)
Out[37]:
Index                128
int64              40000
float64            40000
datetime64[ns]     40000
timedelta64[ns]    40000
complex128         80000
object             40000
bool                5000
categorical         9968
Length: 9, dtype: int64
```

Series.dt accessor

`Series` has gained an accessor to succinctly return datetime like properties for the *values* of the Series, if its a datetime/period like Series. (GH7207) This will return a Series, indexed like the existing Series. See the *docs*

```
# datetime
In [38]: s = pd.Series(pd.date_range('20130101 09:10:12', periods=4))

In [39]: s
Out[39]:
0   2013-01-01 09:10:12
1   2013-01-02 09:10:12
2   2013-01-03 09:10:12
3   2013-01-04 09:10:12
Length: 4, dtype: datetime64[ns]

In [40]: s.dt.hour
Out[40]:
0    9
1    9
2    9
3    9
Length: 4, dtype: int64

In [41]: s.dt.second
Out[41]:
0    12
1    12
2    12
3    12
Length: 4, dtype: int64

In [42]: s.dt.day
Out[42]:
0    1
1    2
2    3
3    4
Length: 4, dtype: int64
```

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```
In [43]: s.dt.freq
Out[43]: 'D'
```

This enables nice expressions like this:

```
In [44]: s[s.dt.day == 2]
Out[44]:
1   2013-01-02 09:10:12
Length: 1, dtype: datetime64[ns]
```

You can easily produce tz aware transformations:

```
In [45]: stz = s.dt.tz_localize('US/Eastern')

In [46]: stz
Out[46]:
0   2013-01-01 09:10:12-05:00
1   2013-01-02 09:10:12-05:00
2   2013-01-03 09:10:12-05:00
3   2013-01-04 09:10:12-05:00
Length: 4, dtype: datetime64[ns, US/Eastern]

In [47]: stz.dt.tz
Out[47]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [48]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[48]:
0   2013-01-01 04:10:12-05:00
1   2013-01-02 04:10:12-05:00
2   2013-01-03 04:10:12-05:00
3   2013-01-04 04:10:12-05:00
Length: 4, dtype: datetime64[ns, US/Eastern]
```

The `.dt` accessor works for period and timedelta dtypes.

```
# period
In [49]: s = pd.Series(pd.period_range('20130101', periods=4, freq='D'))

In [50]: s
Out[50]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
Length: 4, dtype: period[D]

In [51]: s.dt.year
Out[51]:
0    2013
1    2013
2    2013
3    2013
Length: 4, dtype: int64
```

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```
In [52]: s.dt.day
Out[52]:
0    1
1    2
2    3
3    4
Length: 4, dtype: int64
```

```
# timedelta
In [53]: s = pd.Series(pd.timedelta_range('1 day 00:00:05', periods=4, freq='s'))

In [54]: s
Out[54]:
0   1 days 00:00:05
1   1 days 00:00:06
2   1 days 00:00:07
3   1 days 00:00:08
Length: 4, dtype: timedelta64[ns]

In [55]: s.dt.days
Out[55]:
0    1
1    1
2    1
3    1
Length: 4, dtype: int64

In [56]: s.dt.seconds
Out[56]:
0    5
1    6
2    7
3    8
Length: 4, dtype: int64

In [57]: s.dt.components
Out[57]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0     1      0        0        5             0             0            0
1     1      0        0        6             0             0            0
2     1      0        0        7             0             0            0
3     1      0        0        8             0             0            0

[4 rows x 7 columns]
```

Timezone handling improvements

- `tz_localize(None)` for tz-aware `Timestamp` and `DatetimeIndex` now removes timezone holding local time, previously this resulted in `Exception` or `TypeError` (GH7812)

```
In [58]: ts = pd.Timestamp('2014-08-01 09:00', tz='US/Eastern')

In [59]: ts
Out[59]: Timestamp('2014-08-01 09:00:00-0400', tz='US/Eastern')
```

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```
In [60]: ts.tz_localize(None)
Out[60]: Timestamp('2014-08-01 09:00:00')

In [61]: didx = pd.date_range(start='2014-08-01 09:00', freq='H',
   ....:                      periods=10, tz='US/Eastern')
   ....:

In [62]: didx
Out[62]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
               '2014-08-01 11:00:00-04:00', '2014-08-01 12:00:00-04:00',
               '2014-08-01 13:00:00-04:00', '2014-08-01 14:00:00-04:00',
               '2014-08-01 15:00:00-04:00', '2014-08-01 16:00:00-04:00',
               '2014-08-01 17:00:00-04:00', '2014-08-01 18:00:00-04:00'],
              dtype='datetime64[ns, US/Eastern]', freq='H')

In [63]: didx.tz_localize(None)
Out[63]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
               '2014-08-01 11:00:00', '2014-08-01 12:00:00',
               '2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00'],
              dtype='datetime64[ns]', freq=None)
```

- `tz_localize` now accepts the `ambiguous` keyword which allows for passing an array of bools indicating whether the date belongs in DST or not, 'NaT' for setting transition times to NaT, 'infer' for inferring DST/non-DST, and 'raise' (default) for an `AmbiguousTimeError` to be raised. See *the docs* for more details (GH7943)
- `DataFrame.tz_localize` and `DataFrame.tz_convert` now accepts an optional `level` argument for localizing a specific level of a MultiIndex (GH7846)
- `Timestamp.tz_localize` and `Timestamp.tz_convert` now raise `TypeError` in error cases, rather than `Exception` (GH8025)
- a timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone (rather than being a naive `datetime64[ns]`) as `object` dtype (GH8411)
- `Timestamp.__repr__` displays `dateutil.tz.tzoffset` info (GH7907)

Rolling/expanding moments improvements

- `rolling_min()`, `rolling_max()`, `rolling_cov()`, and `rolling_corr()` now return objects with all `NaN` when `len(arg) < min_periods <= window` rather than raising. (This makes all rolling functions consistent in this behavior). (GH7766)

  Prior to 0.15.0

```
In [64]: s = pd.Series([10, 11, 12, 13])
```

```
In [15]: pd.rolling_min(s, window=10, min_periods=5)
ValueError: min_periods (5) must be <= window (4)
```

  New behavior

```
In [4]: pd.rolling_min(s, window=10, min_periods=5)
Out[4]:
0   NaN
1   NaN
2   NaN
3   NaN
dtype: float64
```

- `rolling_max()`, `rolling_min()`, `rolling_sum()`, `rolling_mean()`, `rolling_median()`, `rolling_std()`, `rolling_var()`, `rolling_skew()`, `rolling_kurt()`, `rolling_quantile()`, `rolling_cov()`, `rolling_corr()`, `rolling_corr_pairwise()`, `rolling_window()`, and `rolling_apply()` with `center=True` previously would return a result of the same structure as the input `arg` with `NaN` in the final `(window-1)/2` entries.

  Now the final `(window-1)/2` entries of the result are calculated as if the input `arg` were followed by `(window-1)/2` `NaN` values (or with shrinking windows, in the case of `rolling_apply()`). (GH7925, GH8269)

  Prior behavior (note final value is `NaN`):

```
In [7]: pd.rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[7]:
0     1
1     3
2     6
3   NaN
dtype: float64
```

  New behavior (note final value is `5 = sum([2, 3, NaN])`):

```
In [7]: pd.rolling_sum(pd.Series(range(4)), window=3,
  ....:                min_periods=0, center=True)
Out[7]:
0    1
1    3
2    6
3    5
dtype: float64
```

- `rolling_window()` now normalizes the weights properly in rolling mean mode (*mean=True*) so that the calculated weighted means (e.g. 'triang', 'gaussian') are distributed about the same means as those calculated without weighting (i.e. 'boxcar'). See *the note on normalization* for further details. (GH7618)

```
In [65]: s = pd.Series([10.5, 8.8, 11.4, 9.7, 9.3])
```

  Behavior prior to 0.15.0:

```
In [39]: pd.rolling_window(s, window=3, win_type='triang', center=True)
Out[39]:
0         NaN
1    6.583333
2    6.883333
3    6.683333
4         NaN
dtype: float64
```

  New behavior

```
In [10]: pd.rolling_window(s, window=3, win_type='triang', center=True)
Out[10]:
0       NaN
1     9.875
2    10.325
3    10.025
4       NaN
dtype: float64
```

- Removed `center` argument from all `expanding_` functions (see *list*), as the results produced when `center=True` did not make much sense. (GH7925)
- Added optional `ddof` argument to `expanding_cov()` and `rolling_cov()`. The default value of `1` is backwards-compatible. (GH8279)
- Documented the `ddof` argument to `expanding_var()`, `expanding_std()`, `rolling_var()`, and `rolling_std()`. These functions' support of a `ddof` argument (with a default value of `1`) was previously undocumented. (GH8064)
- `ewma()`, `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now interpret `min_periods` in the same manner that the `rolling_*()` and `expanding_*()` functions do: a given result entry will be `NaN` if the (expanding, in this case) window does not contain at least `min_periods` values. The previous behavior was to set to `NaN` the `min_periods` entries starting with the first non- `NaN` value. (GH7977)

  Prior behavior (note values start at index `2`, which is `min_periods` after index `0` (the index of the first non-empty value)):

```
In [66]: s  = pd.Series([1, None, None, None, 2, 3])
```

```
In [51]: ewma(s, com=3., min_periods=2)
Out[51]:
0         NaN
1         NaN
2    1.000000
3    1.000000
4    1.571429
5    2.189189
dtype: float64
```

  New behavior (note values start at index `4`, the location of the 2nd (since `min_periods=2`) non-empty value):

```
In [2]: pd.ewma(s, com=3., min_periods=2)
Out[2]:
0         NaN
1         NaN
2         NaN
3         NaN
4    1.759644
5    2.383784
dtype: float64
```

- `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `adjust` argument, just like `ewma()` does, affecting how the weights are calculated. The default value of `adjust` is `True`, which is backwards-compatible. See *Exponentially weighted moment functions* for details. (GH7911)
- `ewma()`, `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `ignore_na` argument. When `ignore_na=False` (the default), missing values are taken into account in

the weights calculation. When `ignore_na=True` (which reproduces the pre-0.15.0 behavior), missing values are ignored in the weights calculation. (GH7543)

```
In [7]: pd.ewma(pd.Series([None, 1., 8.]), com=2.)
Out[7]:
0    NaN
1    1.0
2    5.2
dtype: float64

In [8]: pd.ewma(pd.Series([1., None, 8.]), com=2.,
   ....:          ignore_na=True)  # pre-0.15.0 behavior
Out[8]:
0    1.0
1    1.0
2    5.2
dtype: float64

In [9]: pd.ewma(pd.Series([1., None, 8.]), com=2.,
   ....:          ignore_na=False)  # new default
Out[9]:
0    1.000000
1    1.000000
2    5.846154
dtype: float64
```

Warning: By default (`ignore_na=False`) the `ewm*()` functions' weights calculation in the presence of missing values is different than in pre-0.15.0 versions. To reproduce the pre-0.15.0 calculation of weights in the presence of missing values one must specify explicitly `ignore_na=True`.

- Bug in `expanding_cov()`, `expanding_corr()`, `rolling_cov()`, `rolling_cor()`, `ewmcov()`, and `ewmcorr()` returning results with columns sorted by name and producing an error for non-unique columns; now handles non-unique columns and returns columns in original order (except for the case of two DataFrames with `pairwise=False`, where behavior is unchanged) (GH7542)
- Bug in `rolling_count()` and `expanding_*()` functions unnecessarily producing error message for zero-length data (GH8056)
- Bug in `rolling_apply()` and `expanding_apply()` interpreting `min_periods=0` as `min_periods=1` (GH8080)
- Bug in `expanding_std()` and `expanding_var()` for a single value producing a confusing error message (GH7900)
- Bug in `rolling_std()` and `rolling_var()` for a single value producing `0` rather than `NaN` (GH7900)
- Bug in `ewmstd()`, `ewmvol()`, `ewmvar()`, and `ewmcov()` calculation of de-biasing factors when `bias=False` (the default). Previously an incorrect constant factor was used, based on `adjust=True`, `ignore_na=True`, and an infinite number of observations. Now a different factor is used for each entry, based on the actual weights (analogous to the usual `N/(N-1)` factor). In particular, for a single point a value of `NaN` is returned when `bias=False`, whereas previously a value of (approximately) `0` was returned.

  For example, consider the following pre-0.15.0 results for `ewmvar(..., bias=False)`, and the corresponding debiasing factors:

```
In [67]: s = pd.Series([1., 2., 0., 4.])
```

```
In [89]: ewmvar(s, com=2., bias=False)
Out[89]:
0   -2.775558e-16
1    3.000000e-01
2    9.556787e-01
3    3.585799e+00
dtype: float64

In [90]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
Out[90]:
0    1.25
1    1.25
2    1.25
3    1.25
dtype: float64
```

Note that entry `0` is approximately 0, and the debiasing factors are a constant 1.25. By comparison, the following 0.15.0 results have a `NaN` for entry `0`, and the debiasing factors are decreasing (towards 1.25):

```
In [14]: pd.ewmvar(s, com=2., bias=False)
Out[14]:
0         NaN
1    0.500000
2    1.210526
3    4.089069
dtype: float64

In [15]: pd.ewmvar(s, com=2., bias=False) / pd.ewmvar(s, com=2., bias=True)
Out[15]:
0         NaN
1    2.083333
2    1.583333
3    1.425439
dtype: float64
```

See *Exponentially weighted moment functions* for details. (GH7912)

Improvements in the SQL IO module

- Added support for a `chunksize` parameter to `to_sql` function. This allows DataFrame to be written in chunks and avoid packet-size overflow errors (GH8062).
- Added support for a `chunksize` parameter to `read_sql` function. Specifying this argument will return an iterator through chunks of the query result (GH2908).
- Added support for writing `datetime.date` and `datetime.time` object columns with `to_sql` (GH6932).
- Added support for specifying a `schema` to read from/write to with `read_sql_table` and `to_sql` (GH7441, GH7952). For example:

```
df.to_sql('table', engine, schema='other_schema')  # noqa F821
pd.read_sql_table('table', engine, schema='other_schema')  # noqa F821
```

- Added support for writing `NaN` values with `to_sql` (GH2754).
- Added support for writing datetime64 columns with `to_sql` for all database flavors (GH7103).

Backwards incompatible API changes

Breaking changes

API changes related to `Categorical` (see *here* for more details):

- The `Categorical` constructor with two arguments changed from "codes/labels and levels" to "values and levels (now called 'categories')". This can lead to subtle bugs. If you use *`Categorical`* directly, please audit your code by changing it to use the *`from_codes()`* constructor.

  An old function call like (prior to 0.15.0):

```
pd.Categorical([0,1,0,2,1], levels=['a', 'b', 'c'])
```

  will have to adapted to the following to keep the same behaviour:

```
In [2]: pd.Categorical.from_codes([0,1,0,2,1], categories=['a', 'b', 'c'])
Out[2]:
[a, b, a, c, b]
Categories (3, object): [a, b, c]
```

API changes related to the introduction of the `Timedelta` scalar (see *above* for more details):

- Prior to 0.15.0 *`to_timedelta()`* would return a `Series` for list-like/Series input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for Series input, and `Timedelta` for scalar input.

For API changes related to the rolling and expanding functions, see detailed overview *above*.

Other notable API changes:

- Consistency when indexing with `.loc` and a list-like indexer when no values are found.

```
In [68]: df = pd.DataFrame([['a'], ['b']], index=[1, 2])

In [69]: df
Out[69]:
   0
1  a
2  b

[2 rows x 1 columns]
```

  In prior versions there was a difference in these two constructs:

  - `df.loc[[3]]` would return a frame reindexed by 3 (with all `np.nan` values)
  - `df.loc[[3],:]` would raise `KeyError`.

  Both will now raise a `KeyError`. The rule is that *at least 1* indexer must be found when using a list-like and `.loc` (GH7999)

  Furthermore in prior versions these were also different:

  - `df.loc[[1,3]]` would return a frame reindexed by [1,3]
  - `df.loc[[1,3],:]` would raise `KeyError`.

  Both will now return a frame reindex by [1,3]. E.g.

```
In [3]: df.loc[[1, 3]]
Out[3]:
     0
1    a
3  NaN

In [4]: df.loc[[1, 3], :]
Out[4]:
     0
1    a
3  NaN
```

This can also be seen in multi-axis indexing with a `Panel`.

```
>>> p = pd.Panel(np.arange(2 * 3 * 4).reshape(2, 3, 4),
...              items=['ItemA', 'ItemB'],
...              major_axis=[1, 2, 3],
...              minor_axis=['A', 'B', 'C', 'D'])
>>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemB
Major_axis axis: 1 to 3
Minor_axis axis: A to D
```

The following would raise `KeyError` prior to 0.15.0:

```
In [5]:
Out[5]:
   ItemA  ItemD
1      3    NaN
2      7    NaN
3     11    NaN
```

Furthermore, `.loc` will raise If no values are found in a MultiIndex with a list-like indexer:

```
In [70]: s = pd.Series(np.arange(3, dtype='int64'),
   ....:               index=pd.MultiIndex.from_product([['A'],
   ....:                                                 ['foo', 'bar', 'baz']],
   ....:                                                 names=['one', 'two'])
   ....:               ).sort_index()
   ....:

In [71]: s
Out[71]:
one  two
A    bar    1
     baz    2
     foo    0
Length: 3, dtype: int64

In [72]: try:
   ....:     s.loc[['D']]
   ....: except KeyError as e:
   ....:     print("KeyError: " + str(e))
   ....:
KeyError: "['D'] not in index"
```

- Assigning values to `None` now considers the dtype when choosing an 'empty' value (GH7941).

  Previously, assigning to `None` in numeric containers changed the dtype to object (or errored, depending on the call). It now uses `NaN`:

```
In [73]: s = pd.Series([1, 2, 3])

In [74]: s.loc[0] = None

In [75]: s
Out[75]:
0    NaN
1    2.0
2    3.0
Length: 3, dtype: float64
```

  `NaT` is now used similarly for datetime containers.

  For object containers, we now preserve `None` values (previously these were converted to `NaN` values).

```
In [76]: s = pd.Series(["a", "b", "c"])

In [77]: s.loc[0] = None

In [78]: s
Out[78]:
0    None
1       b
2       c
Length: 3, dtype: object
```

  To insert a `NaN`, you must explicitly use `np.nan`. See the *docs*.

- In prior versions, updating a pandas object inplace would not reflect in other python references to this object. (GH8511, GH5104)

```
In [79]: s = pd.Series([1, 2, 3])

In [80]: s2 = s

In [81]: s += 1.5
```

  Behavior prior to v0.15.0

```
# the original object
In [5]: s
Out[5]:
0    2.5
1    3.5
2    4.5
dtype: float64


# a reference to the original object
In [7]: s2
Out[7]:
0    1
1    2
```

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```
2    3
dtype: int64
```

This is now the correct behavior

```
# the original object
In [82]: s
Out[82]:
0    2.5
1    3.5
2    4.5
Length: 3, dtype: float64

# a reference to the original object
In [83]: s2
Out[83]:
0    2.5
1    3.5
2    4.5
Length: 3, dtype: float64
```

- Made both the C-based and Python engines for `read_csv` and `read_table` ignore empty lines in input as well as white space-filled lines, as long as `sep` is not white space. This is an API change that can be controlled by the keyword parameter `skip_blank_lines`. See *the docs* (GH4466)
- A timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone and inserted as `object` dtype rather than being converted to a naive `datetime64[ns]` (GH8411).
- Bug in passing a `DatetimeIndex` with a timezone that was not being retained in DataFrame construction from a dict (GH7822)

  In prior versions this would drop the timezone, now it retains the timezone, but gives a column of `object` dtype:

```
In [84]: i = pd.date_range('1/1/2011', periods=3, freq='10s', tz='US/Eastern')

In [85]: i
Out[85]:
DatetimeIndex(['2011-01-01 00:00:00-05:00', '2011-01-01 00:00:10-05:00',
               '2011-01-01 00:00:20-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='10S')

In [86]: df = pd.DataFrame({'a': i})

In [87]: df
Out[87]:
                          a
0 2011-01-01 00:00:00-05:00
1 2011-01-01 00:00:10-05:00
2 2011-01-01 00:00:20-05:00

[3 rows x 1 columns]

In [88]: df.dtypes
Out[88]:
a    datetime64[ns, US/Eastern]
Length: 1, dtype: object
```

Previously this would have yielded a column of `datetime64` dtype, but without timezone info.

The behaviour of assigning a column to an existing dataframe as `df['a'] = i` remains unchanged (this already returned an `object` column with a timezone).

- When passing multiple levels to *`stack()`*, it will now raise a `ValueError` when the levels aren't all level names or all level numbers (GH7660). See *Reshaping by stacking and unstacking*.
- Raise a `ValueError` in `df.to_hdf` with 'fixed' format, if `df` has non-unique columns as the resulting file will be broken (GH7761)
- `SettingWithCopy` raise/warnings (according to the option `mode.chained_assignment`) will now be issued when setting a value on a sliced mixed-dtype DataFrame using chained-assignment. (GH7845, GH7950)

```
In [1]: df = pd.DataFrame(np.arange(0, 9), columns=['count'])

In [2]: df['group'] = 'b'

In [3]: df.iloc[0:5]['group'] = 'a'
/usr/local/bin/ipython:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
↪stable/indexing.html#indexing-view-versus-copy
```

- `merge`, `DataFrame.merge`, and `ordered_merge` now return the same type as the `left` argument (GH7737).
- Previously an enlargement with a mixed-dtype frame would act unlike `.append` which will preserve dtypes (related GH2578, GH8176):

```
In [89]: df = pd.DataFrame([[True, 1], [False, 2]],
   ....:                   columns=["female", "fitness"])
   ....:

In [90]: df
Out[90]:
   female  fitness
0    True        1
1   False        2

[2 rows x 2 columns]

In [91]: df.dtypes
Out[91]:
female      bool
fitness    int64
Length: 2, dtype: object

# dtypes are now preserved
In [92]: df.loc[2] = df.loc[1]

In [93]: df
Out[93]:
   female  fitness
0    True        1
1   False        2
2   False        2
```

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```
[3 rows x 2 columns]

In [94]: df.dtypes
Out[94]:
female      bool
fitness    int64
Length: 2, dtype: object
```

- `Series.to_csv()` now returns a string when `path=None`, matching the behaviour of `DataFrame.to_csv()` (GH8215).
- `read_hdf` now raises `IOError` when a file that doesn't exist is passed in. Previously, a new, empty file was created, and a `KeyError` raised (GH7715).
- `DataFrame.info()` now ends its output with a newline character (GH8114)
- Concatenating no objects will now raise a `ValueError` rather than a bare `Exception`.
- Merge errors will now be sub-classes of `ValueError` rather than raw `Exception` (GH8501)
- `DataFrame.plot` and `Series.plot` keywords are now have consistent orders (GH8037)

Internal refactoring

In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (GH5080, GH7439, GH7796, GH8024, GH8367, GH7997, GH8522):

- you may need to unpickle pandas version < 0.15.0 pickles using `pd.read_pickle` rather than `pickle.load`. See *pickle docs*
- when plotting with a `PeriodIndex`, the matplotlib internal axes will now be arrays of `Period` rather than a `PeriodIndex` (this is similar to how a `DatetimeIndex` passes arrays of `datetimes` now)
- MultiIndexes will now raise similarly to other pandas objects w.r.t. truth testing, see *here* (GH7897).
- When plotting a DatetimeIndex directly with matplotlib's `plot` function, the axis labels will no longer be formatted as dates but as integers (the internal representation of a `datetime64`). **UPDATE** This is fixed in 0.15.1, see *here*.

Deprecations

- The attributes `Categorical labels` and `levels` attributes are deprecated and renamed to `codes` and `categories`.
- The `outtype` argument to `pd.DataFrame.to_dict` has been deprecated in favor of `orient`. (GH7840)
- The `convert_dummies` method has been deprecated in favor of `get_dummies` (GH8140)
- The `infer_dst` argument in `tz_localize` will be deprecated in favor of `ambiguous` to allow for more flexibility in dealing with DST transitions. Replace `infer_dst=True` with `ambiguous='infer'` for the same behavior (GH7943). See *the docs* for more details.
- The top-level `pd.value_range` has been deprecated and can be replaced by `.describe()` (GH8481)

- The `Index` set operations `+` and `-` were deprecated in order to provide these for numeric type operations on certain index types. `+` can be replaced by `.union()` or `|`, and `-` by `.difference()`. Further the method name `Index.diff()` is deprecated and can be replaced by `Index.difference()` (GH8226)

```
# +
pd.Index(['a', 'b', 'c']) + pd.Index(['b', 'c', 'd'])

# should be replaced by
pd.Index(['a', 'b', 'c']).union(pd.Index(['b', 'c', 'd']))
```

```
# -
pd.Index(['a', 'b', 'c']) - pd.Index(['b', 'c', 'd'])

# should be replaced by
pd.Index(['a', 'b', 'c']).difference(pd.Index(['b', 'c', 'd']))
```

- The `infer_types` argument to *`read_html()`* now has no effect and is deprecated (GH7762, GH7032).

Removal of prior version deprecations/changes

- Remove `DataFrame.delevel` method in favor of `DataFrame.reset_index`

Enhancements

Enhancements in the importing/exporting of Stata files:

- Added support for bool, uint8, uint16 and uint32 data types in `to_stata` (GH7097, GH7365)
- Added conversion option when importing Stata files (GH8527)
- `DataFrame.to_stata` and `StataWriter` check string length for compatibility with limitations imposed in dta files where fixed-width strings must contain 244 or fewer characters. Attempting to write Stata dta files with strings longer than 244 characters raises a `ValueError`. (GH7858)
- `read_stata` and `StataReader` can import missing data information into a `DataFrame` by setting the argument `convert_missing` to `True`. When using this options, missing values are returned as `StataMissingValue` objects and columns containing missing values have `object` data type. (GH8045)

Enhancements in the plotting functions:

- Added `layout` keyword to `DataFrame.plot`. You can pass a tuple of `(rows, columns)`, one of which can be `-1` to automatically infer (GH6667, GH8071).
- Allow to pass multiple axes to `DataFrame.plot`, `hist` and `boxplot` (GH5353, GH6970, GH7069)
- Added support for `c`, `colormap` and `colorbar` arguments for `DataFrame.plot` with `kind='scatter'` (GH7780)
- Histogram from `DataFrame.plot` with `kind='hist'` (GH7809), See *the docs*.
- Boxplot from `DataFrame.plot` with `kind='box'` (GH7998), See *the docs*.

Other:

- `read_csv` now has a keyword parameter `float_precision` which specifies which floating-point converter the C engine should use during parsing, see *here* (GH8002, GH8044)
- Added `searchsorted` method to `Series` objects (GH7447)

- `describe()` on mixed-types DataFrames is more flexible. Type-based column filtering is now possible via the `include`/`exclude` arguments. See the *docs* (GH8164).

```
In [95]: df = pd.DataFrame({'catA': ['foo', 'foo', 'bar'] * 8,
   ....:                    'catB': ['a', 'b', 'c', 'd'] * 6,
   ....:                    'numC': np.arange(24),
   ....:                    'numD': np.arange(24.) + .5})
   ....:

In [96]: df.describe(include=["object"])
Out[96]:
       catA catB
count    24   24
unique    2    4
top     foo    d
freq     16    6

[4 rows x 2 columns]

In [97]: df.describe(include=["number", "object"], exclude=["float"])
Out[97]:
       catA catB       numC
count    24   24  24.000000
unique    2    4        NaN
top     foo    d        NaN
freq     16    6        NaN
mean    NaN  NaN  11.500000
std     NaN  NaN   7.071068
min     NaN  NaN   0.000000
25%     NaN  NaN   5.750000
50%     NaN  NaN  11.500000
75%     NaN  NaN  17.250000
max     NaN  NaN  23.000000

[11 rows x 3 columns]
```

Requesting all columns is possible with the shorthand 'all'

```
In [98]: df.describe(include='all')
Out[98]:
       catA catB       numC       numD
count    24   24  24.000000  24.000000
unique    2    4        NaN        NaN
top     foo    d        NaN        NaN
freq     16    6        NaN        NaN
mean    NaN  NaN  11.500000  12.000000
std     NaN  NaN   7.071068   7.071068
min     NaN  NaN   0.000000   0.500000
25%     NaN  NaN   5.750000   6.250000
50%     NaN  NaN  11.500000  12.000000
75%     NaN  NaN  17.250000  17.750000
max     NaN  NaN  23.000000  23.500000

[11 rows x 4 columns]
```

Without those arguments, `describe` will behave as before, including only numerical columns or, if none are, only categorical columns. See also the *docs*

- Added `split` as an option to the `orient` argument in `pd.DataFrame.to_dict`. (GH7840)

- The `get_dummies` method can now be used on DataFrames. By default only categorical columns are encoded as 0's and 1's, while other columns are left untouched.

```
In [99]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
   ....:                    'C': [1, 2, 3]})
   ....:

In [100]: pd.get_dummies(df)
Out[100]:
   C  A_a  A_b  B_b  B_c
0  1    1    0    0    1
1  2    0    1    0    1
2  3    1    0    1    0

[3 rows x 5 columns]
```

- `PeriodIndex` supports `resolution` as the same as `DatetimeIndex` (GH7708)
- `pandas.tseries.holiday` has added support for additional holidays and ways to observe holidays (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a list of offsets in Python3 (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a days_of_week parameter (GH7070)
- `GroupBy.nth()` now supports selecting multiple nth values (GH7910)

```
In [101]: business_dates = pd.date_range(start='4/1/2014', end='6/30/2014', freq=
↪'B')

In [102]: df = pd.DataFrame(1, index=business_dates, columns=['a', 'b'])

# get the first, 4th, and last date index for each month
In [103]: df.groupby([df.index.year, df.index.month]).nth([0, 3, -1])
Out[103]:
        a  b
2014 4  1  1
     4  1  1
     4  1  1
     5  1  1
     5  1  1
     5  1  1
     6  1  1
     6  1  1
     6  1  1

[9 rows x 2 columns]
```

- `Period` and `PeriodIndex` supports addition/subtraction with `timedelta`-likes (GH7966)

  If `Period` freq is `D`, `H`, `T`, `S`, `L`, `U`, `N`, `Timedelta`-like can be added if the result can have same freq. Otherwise, only the same `offsets` can be added.

```
In [104]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')

In [105]: idx
Out[105]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
             '2014-07-01 12:00', '2014-07-01 13:00'],
```

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```
            dtype='period[H]', freq='H')

In [106]: idx + pd.offsets.Hour(2)
Out[106]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='period[H]', freq='H')

In [107]: idx + pd.Timedelta('120m')
Out[107]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='period[H]', freq='H')

In [108]: idx = pd.period_range('2014-07', periods=5, freq='M')

In [109]: idx
Out[109]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'],␣
↪dtype='period[M]', freq='M')

In [110]: idx + pd.offsets.MonthEnd(3)
Out[110]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'],␣
↪dtype='period[M]', freq='M')
```

- Added experimental compatibility with `openpyxl` for versions >= 2.0. The `DataFrame.to_excel` method `engine` keyword now recognizes `openpyxl1` and `openpyxl2` which will explicitly require openpyxl v1 and v2 respectively, failing if the requested version is not available. The `openpyxl` engine is a now a meta-engine that automatically uses whichever version of openpyxl is installed. (GH7177)
- `DataFrame.fillna` can now accept a `DataFrame` as a fill value (GH8377)
- Passing multiple levels to *`stack()`* will now work when multiple level numbers are passed (GH7660). See *Reshaping by stacking and unstacking*.
- `set_names()`, `set_labels()`, and `set_levels()` methods now take an optional `level` keyword argument to all modification of specific level(s) of a MultiIndex. Additionally `set_names()` now accepts a scalar string value when operating on an `Index` or on a specific level of a `MultiIndex` (GH7792)

```
In [111]: idx = pd.MultiIndex.from_product([['a'], range(3), list("pqr")],
   .....:                                  names=['foo', 'bar', 'baz'])
   .....:

In [112]: idx.set_names('qux', level=0)
Out[112]:
MultiIndex([('a', 0, 'p'),
            ('a', 0, 'q'),
            ('a', 0, 'r'),
            ('a', 1, 'p'),
            ('a', 1, 'q'),
            ('a', 1, 'r'),
            ('a', 2, 'p'),
            ('a', 2, 'q'),
            ('a', 2, 'r')],
           names=['qux', 'bar', 'baz'])

In [113]: idx.set_names(['qux', 'corge'], level=[0, 1])
Out[113]:
```

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```
MultiIndex([('a', 0, 'p'),
            ('a', 0, 'q'),
            ('a', 0, 'r'),
            ('a', 1, 'p'),
            ('a', 1, 'q'),
            ('a', 1, 'r'),
            ('a', 2, 'p'),
            ('a', 2, 'q'),
            ('a', 2, 'r')],
           names=['qux', 'corge', 'baz'])

In [114]: idx.set_levels(['a', 'b', 'c'], level='bar')
Out[114]:
MultiIndex([('a', 'a', 'p'),
            ('a', 'a', 'q'),
            ('a', 'a', 'r'),
            ('a', 'b', 'p'),
            ('a', 'b', 'q'),
            ('a', 'b', 'r'),
            ('a', 'c', 'p'),
            ('a', 'c', 'q'),
            ('a', 'c', 'r')],
           names=['foo', 'bar', 'baz'])

In [115]: idx.set_levels([['a', 'b', 'c'], [1, 2, 3]], level=[1, 2])
Out[115]:
MultiIndex([('a', 'a', 1),
            ('a', 'a', 2),
            ('a', 'a', 3),
            ('a', 'b', 1),
            ('a', 'b', 2),
            ('a', 'b', 3),
            ('a', 'c', 1),
            ('a', 'c', 2),
            ('a', 'c', 3)],
           names=['foo', 'bar', 'baz'])
```

- `Index.isin` now supports a `level` argument to specify which index level to use for membership tests (GH7892, GH7890)

```
In [1]: idx = pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']])

In [2]: idx.values
Out[2]: array([(0, 'a'), (0, 'b'), (0, 'c'), (1, 'a'), (1, 'b'), (1, 'c')],␣
↪dtype=object)

In [3]: idx.isin(['a', 'c', 'e'], level=1)
Out[3]: array([ True, False,  True,  True, False,  True], dtype=bool)
```

- `Index` now supports `duplicated` and `drop_duplicates`. (GH4060)

```
In [116]: idx = pd.Index([1, 2, 3, 4, 1, 2])

In [117]: idx
Out[117]: Int64Index([1, 2, 3, 4, 1, 2], dtype='int64')
```

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```
In [118]: idx.duplicated()
Out[118]: array([False, False, False, False,  True,  True])

In [119]: idx.drop_duplicates()
Out[119]: Int64Index([1, 2, 3, 4], dtype='int64')
```

- add `copy=True` argument to `pd.concat` to enable pass through of complete blocks (GH8252)
- Added support for numpy 1.8+ data types (`bool_`, `int_`, `float_`, `string_`) for conversion to R dataframe (GH8400)

Performance

- Performance improvements in `DatetimeIndex.__iter__` to allow faster iteration (GH7683)
- Performance improvements in `Period` creation (and `PeriodIndex` setitem) (GH5155)
- Improvements in Series.transform for significant performance gains (revised) (GH6496)
- Performance improvements in `StataReader` when reading large files (GH8040, GH8073)
- Performance improvements in `StataWriter` when writing large files (GH8079)
- Performance and memory usage improvements in multi-key `groupby` (GH8128)
- Performance improvements in groupby `.agg` and `.apply` where builtins max/min were not mapped to numpy/cythonized versions (GH7722)
- Performance improvement in writing to sql (`to_sql`) of up to 50% (GH8208).
- Performance benchmarking of groupby for large value of ngroups (GH6787)
- Performance improvement in `CustomBusinessDay`, `CustomBusinessMonth` (GH8236)
- Performance improvement for `MultiIndex.values` for multi-level indexes containing datetimes (GH8543)

Bug fixes

- Bug in pivot_table, when using margins and a dict aggfunc (GH8349)
- Bug in `read_csv` where `squeeze=True` would return a view (GH8217)
- Bug in checking of table name in `read_sql` in certain cases (GH7826).
- Bug in `DataFrame.groupby` where `Grouper` does not recognize level when frequency is specified (GH7885)
- Bug in multiindexes dtypes getting mixed up when DataFrame is saved to SQL table (GH8021)
- Bug in `Series` 0-division with a float and integer operand dtypes (GH7785)
- Bug in `Series.astype("unicode")` not calling `unicode` on the values correctly (GH7758)
- Bug in `DataFrame.as_matrix()` with mixed `datetime64[ns]` and `timedelta64[ns]` dtypes (GH7778)
- Bug in `HDFStore.select_column()` not preserving UTC timezone info when selecting a `DatetimeIndex` (GH7777)
- Bug in `to_datetime` when `format='%Y%m%d'` and `coerce=True` are specified, where previously an object array was returned (rather than a coerced time-series with `NaT`), (GH7930)

- Bug in `DatetimeIndex` and `PeriodIndex` in-place addition and subtraction cause different result from normal one (GH6527)
- Bug in adding and subtracting `PeriodIndex` with `PeriodIndex` raise `TypeError` (GH7741)
- Bug in `combine_first` with `PeriodIndex` data raises `TypeError` (GH3367)
- Bug in MultiIndex slicing with missing indexers (GH7866)
- Bug in MultiIndex slicing with various edge cases (GH8132)
- Regression in MultiIndex indexing with a non-scalar type object (GH7914)
- Bug in `Timestamp` comparisons with == and `int64` dtype (GH8058)
- Bug in pickles contains `DateOffset` may raise `AttributeError` when `normalize` attribute is referred internally (GH7748)
- Bug in `Panel` when using `major_xs` and `copy=False` is passed (deprecation warning fails because of missing `warnings`) (GH8152).
- Bug in pickle deserialization that failed for pre-0.14.1 containers with dup items trying to avoid ambiguity when matching block and manager items, when there's only one block there's no ambiguity (GH7794)
- Bug in putting a `PeriodIndex` into a `Series` would convert to `int64` dtype, rather than `object` of `Periods` (GH7932)
- Bug in `HDFStore` iteration when passing a where (GH8014)
- Bug in `DataFrameGroupby.transform` when transforming with a passed non-sorted key (GH8046, GH8430)
- Bug in repeated timeseries line and area plot may result in `ValueError` or incorrect kind (GH7733)
- Bug in inference in a `MultiIndex` with `datetime.date` inputs (GH7888)
- Bug in `get` where an `IndexError` would not cause the default value to be returned (GH7725)
- Bug in `offsets.apply`, `rollforward` and `rollback` may reset nanosecond (GH7697)
- Bug in `offsets.apply`, `rollforward` and `rollback` may raise `AttributeError` if `Timestamp` has `dateutil` tzinfo (GH7697)
- Bug in sorting a MultiIndex frame with a `Float64Index` (GH8017)
- Bug in inconsistent panel setitem with a rhs of a `DataFrame` for alignment (GH7763)
- Bug in `is_superperiod` and `is_subperiod` cannot handle higher frequencies than `S` (GH7760, GH7772, GH7803)
- Bug in 32-bit platforms with `Series.shift` (GH8129)
- Bug in `PeriodIndex.unique` returns int64 `np.ndarray` (GH7540)
- Bug in `groupby.apply` with a non-affecting mutation in the function (GH8467)
- Bug in `DataFrame.reset_index` which has `MultiIndex` contains `PeriodIndex` or `DatetimeIndex` with tz raises `ValueError` (GH7746, GH7793)
- Bug in `DataFrame.plot` with `subplots=True` may draw unnecessary minor xticks and yticks (GH7801)
- Bug in `StataReader` which did not read variable labels in 117 files due to difference between Stata documentation and implementation (GH7816)
- Bug in `StataReader` where strings were always converted to 244 characters-fixed width irrespective of underlying string size (GH7858)
- Bug in `DataFrame.plot` and `Series.plot` may ignore `rot` and `fontsize` keywords (GH7844)

- Bug in `DatetimeIndex.value_counts` doesn't preserve tz (GH7735)
- Bug in `PeriodIndex.value_counts` results in `Int64Index` (GH7735)
- Bug in `DataFrame.join` when doing left join on index and there are multiple matches (GH5391)
- Bug in `GroupBy.transform()` where int groups with a transform that didn't preserve the index were incorrectly truncated (GH7972).
- Bug in `groupby` where callable objects without name attributes would take the wrong path, and produce a `DataFrame` instead of a `Series` (GH7929)
- Bug in `groupby` error message when a DataFrame grouping column is duplicated (GH7511)
- Bug in `read_html` where the `infer_types` argument forced coercion of date-likes incorrectly (GH7762, GH7032).
- Bug in `Series.str.cat` with an index which was filtered as to not include the first item (GH7857)
- Bug in `Timestamp` cannot parse `nanosecond` from string (GH7878)
- Bug in `Timestamp` with string offset and `tz` results incorrect (GH7833)
- Bug in `tslib.tz_convert` and `tslib.tz_convert_single` may return different results (GH7798)
- Bug in `DatetimeIndex.intersection` of non-overlapping timestamps with tz raises `IndexError` (GH7880)
- Bug in alignment with TimeOps and non-unique indexes (GH8363)
- Bug in `GroupBy.filter()` where fast path vs. slow path made the filter return a non scalar value that appeared valid but wasn't (GH7870).
- Bug in `date_range()`/`DatetimeIndex()` when the timezone was inferred from input dates yet incorrect times were returned when crossing DST boundaries (GH7835, GH7901).
- Bug in `to_excel()` where a negative sign was being prepended to positive infinity and was absent for negative infinity (GH7949)
- Bug in area plot draws legend with incorrect `alpha` when `stacked=True` (GH8027)
- `Period` and `PeriodIndex` addition/subtraction with `np.timedelta64` results in incorrect internal representations (GH7740)
- Bug in `Holiday` with no offset or observance (GH7987)
- Bug in `DataFrame.to_latex` formatting when columns or index is a `MultiIndex` (GH7982).
- Bug in `DateOffset` around Daylight Savings Time produces unexpected results (GH5175).
- Bug in `DataFrame.shift` where empty columns would throw `ZeroDivisionError` on numpy 1.7 (GH8019)
- Bug in installation where `html_encoding/*.html` wasn't installed and therefore some tests were not running correctly (GH7927).
- Bug in `read_html` where `bytes` objects were not tested for in `_read` (GH7927).
- Bug in `DataFrame.stack()` when one of the column levels was a datelike (GH8039)
- Bug in broadcasting numpy scalars with `DataFrame` (GH8116)
- Bug in `pivot_table` performed with nameless `index` and `columns` raises `KeyError` (GH8103)
- Bug in `DataFrame.plot(kind='scatter')` draws points and errorbars with different colors when the color is specified by `c` keyword (GH8081)
- Bug in `Float64Index` where `iat` and `at` were not testing and were failing (GH8092).

- Bug in `DataFrame.boxplot()` where y-limits were not set correctly when producing multiple axes (GH7528, GH5517).
- Bug in `read_csv` where line comments were not handled correctly given a custom line terminator or `delim_whitespace=True` (GH8122).
- Bug in `read_html` where empty tables caused a `StopIteration` (GH7575)
- Bug in casting when setting a column in a same-dtype block (GH7704)
- Bug in accessing groups from a `GroupBy` when the original grouper was a tuple (GH8121).
- Bug in `.at` that would accept integer indexers on a non-integer index and do fallback (GH7814)
- Bug with kde plot and NaNs (GH8182)
- Bug in `GroupBy.count` with float32 data type were nan values were not excluded (GH8169).
- Bug with stacked barplots and NaNs (GH8175).
- Bug in resample with non evenly divisible offsets (e.g. '7s') (GH8371)
- Bug in interpolation methods with the `limit` keyword when no values needed interpolating (GH7173).
- Bug where `col_space` was ignored in `DataFrame.to_string()` when `header=False` (GH8230).
- Bug with `DatetimeIndex.asof` incorrectly matching partial strings and returning the wrong date (GH8245).
- Bug in plotting methods modifying the global matplotlib rcParams (GH8242).
- Bug in `DataFrame.__setitem__` that caused errors when setting a dataframe column to a sparse array (GH8131)
- Bug where `Dataframe.boxplot()` failed when entire column was empty (GH8181).
- Bug with messed variables in `radviz` visualization (GH8199).
- Bug in interpolation methods with the `limit` keyword when no values needed interpolating (GH7173).
- Bug where `col_space` was ignored in `DataFrame.to_string()` when `header=False` (GH8230).
- Bug in `to_clipboard` that would clip long column data (GH8305)
- Bug in `DataFrame` terminal display: Setting max_column/max_rows to zero did not trigger auto-resizing of dfs to fit terminal width/height (GH7180).
- Bug in OLS where running with "cluster" and "nw_lags" parameters did not work correctly, but also did not throw an error (GH5884).
- Bug in `DataFrame.dropna` that interpreted non-existent columns in the subset argument as the 'last column' (GH8303)
- Bug in `Index.intersection` on non-monotonic non-unique indexes (GH8362).
- Bug in masked series assignment where mismatching types would break alignment (GH8387)
- Bug in `NDFrame.equals` gives false negatives with dtype=object (GH8437)
- Bug in assignment with indexer where type diversity would break alignment (GH8258)
- Bug in `NDFrame.loc` indexing when row/column names were lost when target was a list/ndarray (GH6552)
- Regression in `NDFrame.loc` indexing when rows/columns were converted to Float64Index if target was an empty list/ndarray (GH7774)
- Bug in `Series` that allows it to be indexed by a `DataFrame` which has unexpected results. Such indexing is no longer permitted (GH8444)

- Bug in item assignment of a `DataFrame` with MultiIndex columns where right-hand-side columns were not aligned (GH7655)
- Suppress FutureWarning generated by NumPy when comparing object arrays containing NaN for equality (GH7065)
- Bug in `DataFrame.eval()` where the dtype of the `not` operator (`~`) was not correctly inferred as `bool`.

Contributors

A total of 80 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Aaron Schumacher +
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- klonuo +
- lexual
- mcjcode +
- mtrbean +
- onesandzeroes
- rockg
- seth-p
- sinhrks
- someben +
- stahlous +
- stas-sl +
- thatneat +
- tom-alcorn +
- unknown
- unutbu
- zachcp +

5.15 Version 0.14

5.15.1 Version 0.14.1 (July 11, 2014)

This is a minor release from 0.14.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
  - New methods `select_dtypes()` to select columns based on the dtype and `sem()` to calculate the standard error of the mean.
  - Support for dateutil timezones (see *docs*).
  - Support for ignoring full line comments in the `read_csv()` text parser.
  - New documentation section on *Options and Settings*.
  - Lots of bug fixes.
- *Enhancements*
- *API Changes*
- *Performance Improvements*
- *Experimental Changes*
- *Bug Fixes*

API changes

- Openpyxl now raises a ValueError on construction of the openpyxl writer instead of warning on pandas import (GH7284).
- For `StringMethods.extract`, when no match is found, the result - only containing `NaN` values - now also has `dtype=object` instead of `float` (GH7242)
- `Period` objects no longer raise a `TypeError` when compared using `==` with another object that *isn't* a `Period`. Instead when comparing a `Period` with another object using `==` if the other object isn't a `Period` `False` is returned. (GH7376)
- Previously, the behaviour on resetting the time or not in `offsets.apply`, `rollforward` and `rollback` operations differed between offsets. With the support of the `normalize` keyword for all offsets(see below) with a default value of False (preserve time), the behaviour changed for certain offsets (BusinessMonthBegin, MonthEnd, BusinessMonthEnd, CustomBusinessMonthEnd, BusinessYearBegin, LastWeekOfMonth, FY5253Quarter, LastWeekOfMonth, Easter):

```
In [6]: from pandas.tseries import offsets

In [7]: d = pd.Timestamp('2014-01-01 09:00')

# old behaviour < 0.14.1
In [8]: d + offsets.MonthEnd()
Out[8]: pd.Timestamp('2014-01-31 00:00:00')
```

  Starting from 0.14.1 all offsets preserve time by default. The old behaviour can be obtained with `normalize=True`

```
# new behaviour
In [1]: d + offsets.MonthEnd()
Out[1]: Timestamp('2014-01-31 09:00:00')

In [2]: d + offsets.MonthEnd(normalize=True)
Out[2]: Timestamp('2014-01-31 00:00:00')
```

  Note that for the other offsets the default behaviour did not change.

- Add back `#N/A N/A` as a default NA value in text parsing, (regression from 0.12) (GH5521)
- Raise a `TypeError` on inplace-setting with a `.where` and a non `np.nan` value as this is inconsistent with a set-item expression like `df[mask] = None` (GH7656)

Enhancements

- Add `dropna` argument to `value_counts` and `nunique` (GH5569).
- Add *`select_dtypes()`* method to allow selection of columns based on dtype (GH7316). See *the docs*.
- All `offsets` supports the `normalize` keyword to specify whether `offsets.apply`, `rollforward` and `rollback` resets the time (hour, minute, etc) or not (default `False`, preserves time) (GH7156):

```
import pandas.tseries.offsets as offsets

day = offsets.Day()
day.apply(pd.Timestamp("2014-01-01 09:00"))

day = offsets.Day(normalize=True)
day.apply(pd.Timestamp("2014-01-01 09:00"))
```

- `PeriodIndex` is represented as the same format as `DatetimeIndex` (GH7601)
- `StringMethods` now work on empty Series (GH7242)
- The file parsers `read_csv` and `read_table` now ignore line comments provided by the parameter `comment`, which accepts only a single character for the C reader. In particular, they allow for comments before file data begins (GH2685)
- Add `NotImplementedError` for simultaneous use of `chunksize` and `nrows` for read_csv() (GH6774).
- Tests for basic reading of public S3 buckets now exist (GH7281).
- `read_html` now sports an `encoding` argument that is passed to the underlying parser library. You can use this to read non-ascii encoded web pages (GH7323).
- `read_excel` now supports reading from URLs in the same way that `read_csv` does. (GH6809)
- Support for dateutil timezones, which can now be used in the same way as pytz timezones across pandas. (GH4688)

```
In [3]: rng = pd.date_range(
   ...:     "3/6/2012 00:00", periods=10, freq="D", tz="dateutil/Europe/London"
   ...: )
   ...:

In [4]: rng.tz
Out[4]: tzfile('/usr/share/zoneinfo/Europe/London')
```

  See *the docs*.

- Implemented `sem` (standard error of the mean) operation for `Series`, `DataFrame`, `Panel`, and `Groupby` (GH6897)
- Add `nlargest` and `nsmallest` to the `Series` `groupby` allowlist, which means you can now use these methods on a `SeriesGroupBy` object (GH7053).
- All offsets `apply`, `rollforward` and `rollback` can now handle `np.datetime64`, previously results in `ApplyTypeError` (GH7452)
- `Period` and `PeriodIndex` can contain `NaT` in its values (GH7485)
- Support pickling `Series`, `DataFrame` and `Panel` objects with non-unique labels along *item* axis (`index`, `columns` and `items` respectively) (GH7370).
- Improved inference of datetime/timedelta with mixed null objects. Regression from 0.13.1 in interpretation of an object Index with all null elements (GH7431)

Performance

- Improvements in dtype inference for numeric operations involving yielding performance gains for dtypes: `int64`, `timedelta64`, `datetime64` (GH7223)
- Improvements in Series.transform for significant performance gains (GH6496)
- Improvements in DataFrame.transform with ufuncs and built-in grouper functions for significant performance gains (GH7383)
- Regression in groupby aggregation of datetime64 dtypes (GH7555)
- Improvements in `MultiIndex.from_product` for large iterables (GH7627)

Experimental

- `pandas.io.data.Options` has a new method, `get_all_data` method, and now consistently returns a MultiIndexed `DataFrame` (GH5602)
- `io.gbq.read_gbq` and `io.gbq.to_gbq` were refactored to remove the dependency on the Google `bq.py` command line client. This submodule now uses `httplib2` and the Google `apiclient` and `oauth2client` API client libraries which should be more stable and, therefore, reliable than `bq.py`. See *the docs*. (GH6937).

Bug fixes

- Bug in `DataFrame.where` with a symmetric shaped frame and a passed other of a DataFrame (GH7506)
- Bug in Panel indexing with a MultiIndex axis (GH7516)
- Regression in datetimelike slice indexing with a duplicated index and non-exact end-points (GH7523)
- Bug in setitem with list-of-lists and single vs mixed types (GH7551:)
- Bug in time ops with non-aligned Series (GH7500)
- Bug in timedelta inference when assigning an incomplete Series (GH7592)
- Bug in groupby `.nth` with a Series and integer-like column name (GH7559)
- Bug in `Series.get` with a boolean accessor (GH7407)
- Bug in `value_counts` where `NaT` did not qualify as missing (`NaN`) (GH7423)
- Bug in `to_timedelta` that accepted invalid units and misinterpreted 'm/h' (GH7611, GH6423)
- Bug in line plot doesn't set correct `xlim` if `secondary_y=True` (GH7459)
- Bug in grouped `hist` and `scatter` plots use old `figsize` default (GH7394)
- Bug in plotting subplots with `DataFrame.plot`, `hist` clears passed `ax` even if the number of subplots is one (GH7391).
- Bug in plotting subplots with `DataFrame.boxplot` with `by` kw raises `ValueError` if the number of subplots exceeds 1 (GH7391).
- Bug in subplots displays `ticklabels` and `labels` in different rule (GH5897)
- Bug in `Panel.apply` with a MultiIndex as an axis (GH7469)
- Bug in `DatetimeIndex.insert` doesn't preserve `name` and `tz` (GH7299)
- Bug in `DatetimeIndex.asobject` doesn't preserve `name` (GH7299)
- Bug in MultiIndex slicing with datetimelike ranges (strings and Timestamps), (GH7429)
- Bug in `Index.min` and `max` doesn't handle `nan` and `NaT` properly (GH7261)
- Bug in `PeriodIndex.min/max` results in `int` (GH7609)
- Bug in `resample` where `fill_method` was ignored if you passed `how` (GH2073)
- Bug in `TimeGrouper` doesn't exclude column specified by `key` (GH7227)
- Bug in `DataFrame` and `Series` bar and barh plot raises `TypeError` when `bottom` and `left` keyword is specified (GH7226)
- Bug in `DataFrame.hist` raises `TypeError` when it contains non numeric column (GH7277)
- Bug in `Index.delete` does not preserve `name` and `freq` attributes (GH7302)

- Bug in `DataFrame.query()/eval` where local string variables with the @ sign were being treated as temporaries attempting to be deleted (GH7300).
- Bug in `Float64Index` which didn't allow duplicates (GH7149).
- Bug in `DataFrame.replace()` where truthy values were being replaced (GH7140).
- Bug in `StringMethods.extract()` where a single match group Series would use the matcher's name instead of the group name (GH7313).
- Bug in `isnull()` when `mode.use_inf_as_null == True` where isnull wouldn't test `True` when it encountered an `inf`/`-inf` (GH7315).
- Bug in inferred_freq results in None for eastern hemisphere timezones (GH7310)
- Bug in `Easter` returns incorrect date when offset is negative (GH7195)
- Bug in broadcasting with `.div`, integer dtypes and divide-by-zero (GH7325)
- Bug in `CustomBusinessDay.apply` raises `NameError` when `np.datetime64` object is passed (GH7196)
- Bug in `MultiIndex.append`, `concat` and `pivot_table` don't preserve timezone (GH6606)
- Bug in `.loc` with a list of indexers on a single-multi index level (that is not nested) (GH7349)
- Bug in `Series.map` when mapping a dict with tuple keys of different lengths (GH7333)
- Bug all `StringMethods` now work on empty Series (GH7242)
- Fix delegation of `read_sql` to `read_sql_query` when query does not contain 'select' (GH7324).
- Bug where a string column name assignment to a `DataFrame` with a `Float64Index` raised a `TypeError` during a call to `np.isnan` (GH7366).
- Bug where `NDFrame.replace()` didn't correctly replace objects with `Period` values (GH7379).
- Bug in `.ix` getitem should always return a Series (GH7150)
- Bug in MultiIndex slicing with incomplete indexers (GH7399)
- Bug in MultiIndex slicing with a step in a sliced level (GH7400)
- Bug where negative indexers in `DatetimeIndex` were not correctly sliced (GH7408)
- Bug where `NaT` wasn't repr'd correctly in a `MultiIndex` (GH7406, GH7409).
- Bug where bool objects were converted to `nan` in `convert_objects` (GH7416).
- Bug in `quantile` ignoring the axis keyword argument (GH7306)
- Bug where `nanops._maybe_null_out` doesn't work with complex numbers (GH7353)
- Bug in several `nanops` functions when `axis==0` for 1-dimensional `nan` arrays (GH7354)
- Bug where `nanops.nanmedian` doesn't work when `axis==None` (GH7352)
- Bug where `nanops._has_infs` doesn't work with many dtypes (GH7357)
- Bug in `StataReader.data` where reading a 0-observation dta failed (GH7369)
- Bug in `StataReader` when reading Stata 13 (117) files containing fixed width strings (GH7360)
- Bug in `StataWriter` where encoding was ignored (GH7286)
- Bug in `DatetimeIndex` comparison doesn't handle `NaT` properly (GH7529)
- Bug in passing input with `tzinfo` to some offsets `apply`, `rollforward` or `rollback` resets `tzinfo` or raises `ValueError` (GH7465)

- Bug in `DatetimeIndex.to_period`, `PeriodIndex.asobject`, `PeriodIndex.to_timestamp` doesn't preserve `name` (GH7485)
- Bug in `DatetimeIndex.to_period` and `PeriodIndex.to_timestamp` handle `NaT` incorrectly (GH7228)
- Bug in `offsets.apply`, `rollforward` and `rollback` may return normal `datetime` (GH7502)
- Bug in `resample` raises `ValueError` when target contains `NaT` (GH7227)
- Bug in `Timestamp.tz_localize` resets `nanosecond` info (GH7534)
- Bug in `DatetimeIndex.asobject` raises `ValueError` when it contains `NaT` (GH7539)
- Bug in `Timestamp.__new__` doesn't preserve nanosecond properly (GH7610)
- Bug in `Index.astype(float)` where it would return an `object` dtype `Index` (GH7464).
- Bug in `DataFrame.reset_index` loses `tz` (GH3950)
- Bug in `DatetimeIndex.freqstr` raises `AttributeError` when `freq` is `None` (GH7606)
- Bug in `GroupBy.size` created by `TimeGrouper` raises `AttributeError` (GH7453)
- Bug in single column bar plot is misaligned (GH7498).
- Bug in area plot with tz-aware time series raises `ValueError` (GH7471)
- Bug in non-monotonic `Index.union` may preserve `name` incorrectly (GH7458)
- Bug in `DatetimeIndex.intersection` doesn't preserve timezone (GH4690)
- Bug in `rolling_var` where a window larger than the array would raise an error(GH7297)
- Bug with last plotted timeseries dictating `xlim` (GH2960)
- Bug with `secondary_y` axis not being considered for timeseries `xlim` (GH3490)
- Bug in `Float64Index` assignment with a non scalar indexer (GH7586)
- Bug in `pandas.core.strings.str_contains` does not properly match in a case insensitive fashion when `regex=False` and `case=False` (GH7505)
- Bug in `expanding_cov`, `expanding_corr`, `rolling_cov`, and `rolling_corr` for two arguments with mismatched index (GH7512)
- Bug in `to_sql` taking the boolean column as text column (GH7678)
- Bug in grouped `hist` doesn't handle `rot` kw and `sharex` kw properly (GH7234)
- Bug in `.loc` performing fallback integer indexing with `object` dtype indices (GH7496)
- Bug (regression) in `PeriodIndex` constructor when passed `Series` objects (GH7701).

Contributors

A total of 46 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- helger +
- immerrr
- jaimefrio
- jreback
- lexual
- onesandzeroes
- rockg

- sanguineturtle +
- seth-p +
- sinhrks
- unknown
- yelite +

5.15.2 Version 0.14.0 (May 31 , 2014)

This is a major release from 0.13.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
  - Officially support Python 3.4
  - SQL interfaces updated to use `sqlalchemy`, See *Here*.
  - Display interface changes, See *Here*
  - MultiIndexing Using Slicers, See *Here*.
  - Ability to join a singly-indexed DataFrame with a MultiIndexed DataFrame, see *Here*
  - More consistency in groupby results and more flexible groupby specifications, See *Here*
  - Holiday calendars are now supported in `CustomBusinessDay`, see *Here*
  - Several improvements in plotting functions, including: hexbin, area and pie plots, see *Here*.
  - Performance doc section on I/O operations, See *Here*
- *Other Enhancements*
- *API Changes*
- *Text Parsing API Changes*
- *Groupby API Changes*
- *Performance Improvements*
- *Prior Deprecations*
- *Deprecations*
- *Known Issues*
- *Bug Fixes*

Warning: In 0.14.0 all `NDFrame` based containers have undergone significant internal refactoring. Before that each block of homogeneous data had its own labels and extra care was necessary to keep those in sync with the parent container's labels. This should not have any visible user/API behavior changes (GH6745)

API changes

- `read_excel` uses 0 as the default sheet (GH6573)
- `iloc` will now accept out-of-bounds indexers for slices, e.g. a value that exceeds the length of the object being indexed. These will be excluded. This will make pandas conform more with python/numpy indexing of out-of-bounds values. A single indexer that is out-of-bounds and drops the dimensions of the object will still raise `IndexError` (GH6296, GH6299). This could result in an empty axis (e.g. an empty DataFrame being returned)

```
In [1]: dfl = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))

In [2]: dfl
Out[2]:
          A         B
0  0.469112 -0.282863
1 -1.509059 -1.135632
2  1.212112 -0.173215
3  0.119209 -1.044236
4 -0.861849 -2.104569

[5 rows x 2 columns]

In [3]: dfl.iloc[:, 2:3]
Out[3]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

[5 rows x 0 columns]

In [4]: dfl.iloc[:, 1:3]
Out[4]:
          B
0 -0.282863
1 -1.135632
2 -0.173215
3 -1.044236
4 -2.104569

[5 rows x 1 columns]

In [5]: dfl.iloc[4:6]
Out[5]:
          A         B
4 -0.861849 -2.104569

[1 rows x 2 columns]
```

These are out-of-bounds selections

```
>>> dfl.iloc[[4, 5, 6]]
IndexError: positional indexers are out-of-bounds

>>> dfl.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds
```

- Slicing with negative start, stop & step values handles corner cases better (GH6531):

  - `df.iloc[:-len(df)]` is now empty
  - `df.iloc[len(df)::-1]` now enumerates all elements in reverse

- The *`DataFrame.interpolate()`* keyword `downcast` default has been changed from `infer` to `None`. This is to preserve the original dtype unless explicitly requested otherwise (GH6290).
- When converting a dataframe to HTML it used to return `Empty DataFrame`. This special case has been removed, instead a header with the column names is returned (GH6062).
- `Series` and `Index` now internally share more common operations, e.g. `factorize(),nunique(), value_counts()` are now supported on `Index` types as well. The `Series.weekday` property from is removed from Series for API consistency. Using a `DatetimeIndex/PeriodIndex` method on a Series will now raise a `TypeError`. (GH4551, GH4056, GH5519, GH6380, GH7206).
- Add `is_month_start, is_month_end, is_quarter_start, is_quarter_end, is_year_start, is_year_end` accessors for `DateTimeIndex / Timestamp` which return a boolean array of whether the timestamp(s) are at the start/end of the month/quarter/year defined by the frequency of the `DateTimeIndex / Timestamp` (GH4565, GH6998)
- Local variable usage has changed in *`pandas.eval()`*/*`DataFrame.eval()`*/*`DataFrame.query()`* (GH5987). For the *`DataFrame`* methods, two things have changed
  - Column names are now given precedence over locals
  - Local variables must be referred to explicitly. This means that even if you have a local variable that is *not* a column you must still refer to it with the `'@'` prefix.
  - You can have an expression like `df.query('@a < a')` with no complaints from `pandas` about ambiguity of the name `a`.
  - The top-level *`pandas.eval()`* function does not allow you use the `'@'` prefix and provides you with an error message telling you so.
  - `NameResolutionError` was removed because it isn't necessary anymore.
- Define and document the order of column vs index names in query/eval (GH6676)
- `concat` will now concatenate mixed Series and DataFrames using the Series name or numbering columns as needed (GH2385). See *the docs*
- Slicing and advanced/boolean indexing operations on `Index` classes as well as *`Index.delete()`* and *`Index.drop()`* methods will no longer change the type of the resulting index (GH6440, GH7040)

```
In [6]: i = pd.Index([1, 2, 3, 'a', 'b', 'c'])

In [7]: i[[0, 1, 2]]
Out[7]: Index([1, 2, 3], dtype='object')

In [8]: i.drop(['a', 'b', 'c'])
Out[8]: Index([1, 2, 3], dtype='object')
```

  Previously, the above operation would return `Int64Index`. If you'd like to do this manually, use *`Index.astype()`*

```
In [9]: i[[0, 1, 2]].astype(np.int_)
Out[9]: Int64Index([1, 2, 3], dtype='int64')
```

- `set_index` no longer converts MultiIndexes to an Index of tuples. For example, the old behavior returned an Index in this case (GH6459):

```
# Old behavior, casted MultiIndex to an Index
In [10]: tuple_ind
Out[10]: Index([('a', 'c'), ('a', 'd'), ('b', 'c'), ('b', 'd')], dtype='object')

In [11]: df_multi.set_index(tuple_ind)
Out[11]:
                0         1
(a, c)  0.471435 -1.190976
(a, d)  1.432707 -0.312652
(b, c) -0.720589  0.887163
(b, d)  0.859588 -0.636524

[4 rows x 2 columns]

# New behavior
In [12]: mi
Out[12]:
MultiIndex([('a', 'c'),
            ('a', 'd'),
            ('b', 'c'),
            ('b', 'd')],
           )

In [13]: df_multi.set_index(mi)
Out[13]:
             0         1
a c  0.471435 -1.190976
  d  1.432707 -0.312652
b c -0.720589  0.887163
  d  0.859588 -0.636524

[4 rows x 2 columns]
```

This also applies when passing multiple indices to `set_index`:

```
# Old output, 2-level MultiIndex of tuples
In [14]: df_multi.set_index([df_multi.index, df_multi.index])
Out[14]:
                        0         1
(a, c) (a, c)  0.471435 -1.190976
(a, d) (a, d)  1.432707 -0.312652
(b, c) (b, c) -0.720589  0.887163
(b, d) (b, d)  0.859588 -0.636524

[4 rows x 2 columns]

# New output, 4-level MultiIndex
In [15]: df_multi.set_index([df_multi.index, df_multi.index])
Out[15]:
                 0         1
a c a c  0.471435 -1.190976
  d a d  1.432707 -0.312652
b c b c -0.720589  0.887163
  d b d  0.859588 -0.636524

[4 rows x 2 columns]
```

- `pairwise` keyword was added to the statistical moment functions `rolling_cov`, `rolling_corr`,

`ewmcov`, `ewmcorr`, `expanding_cov`, `expanding_corr` to allow the calculation of moving window covariance and correlation matrices (GH4950). See *Computing rolling pairwise covariances and correlations* in the docs.

```
In [1]: df = pd.DataFrame(np.random.randn(10, 4), columns=list('ABCD'))

In [4]: covs = pd.rolling_cov(df[['A', 'B', 'C']],
   ....:                      df[['B', 'C', 'D']],
   ....:                      5,
   ....:                      pairwise=True)


In [5]: covs[df.index[-1]]
Out[5]:
          B         C         D
A  0.035310  0.326593 -0.505430
B  0.137748 -0.006888 -0.005383
C -0.006888  0.861040  0.020762
```

- `Series.iteritems()` is now lazy (returns an iterator rather than a list). This was the documented behavior prior to 0.14. (GH6760)
- Added `nunique` and `value_counts` functions to `Index` for counting unique elements. (GH6734)
- `stack` and `unstack` now raise a `ValueError` when the `level` keyword refers to a non-unique item in the `Index` (previously raised a `KeyError`). (GH6738)
- drop unused order argument from `Series.sort`; args now are in the same order as `Series.order`; add `na_position` arg to conform to `Series.order` (GH6847)
- default sorting algorithm for `Series.order` is now `quicksort`, to conform with `Series.sort` (and numpy defaults)
- add `inplace` keyword to `Series.order/sort` to make them inverses (GH6859)
- `DataFrame.sort` now places NaNs at the beginning or end of the sort according to the `na_position` parameter. (GH3917)
- accept `TextFileReader` in `concat`, which was affecting a common user idiom (GH6583), this was a regression from 0.13.1
- Added `factorize` functions to `Index` and `Series` to get indexer and unique values (GH7090)
- `describe` on a DataFrame with a mix of Timestamp and string like objects returns a different Index (GH7088). Previously the index was unintentionally sorted.
- Arithmetic operations with **only** `bool` dtypes now give a warning indicating that they are evaluated in Python space for `+`, `-`, and `*` operations and raise for all others (GH7011, GH6762, GH7015, GH7210)

```
>>> x = pd.Series(np.random.rand(10) > 0.5)
>>> y = True
>>> x + y  # warning generated: should do x | y instead
UserWarning: evaluating in Python space because the '+' operator is not
supported by numexpr for the bool dtype, use '|' instead
>>> x / y  # this raises because it doesn't make sense
NotImplementedError: operator '/' not implemented for bool dtypes
```

- In `HDFStore`, `select_as_multiple` will always raise a `KeyError`, when a key or the selector is not found (GH6177)
- `df['col'] = value` and `df.loc[:,'col'] = value` are now completely equivalent; previously the `.loc` would not necessarily coerce the dtype of the resultant series (GH6149)

- `dtypes` and `ftypes` now return a series with `dtype=object` on empty containers (GH5740)
- `df.to_csv` will now return a string of the CSV data if neither a target path nor a buffer is provided (GH6061)
- `pd.infer_freq()` will now raise a `TypeError` if given an invalid `Series/Index` type (GH6407, GH6463)
- A tuple passed to `DataFame.sort_index` will be interpreted as the levels of the index, rather than requiring a list of tuple (GH4370)
- all offset operations now return `Timestamp` types (rather than datetime), Business/Week frequencies were incorrect (GH4069)
- `to_excel` now converts `np.inf` into a string representation, customizable by the `inf_rep` keyword argument (Excel has no native inf representation) (GH6782)
- Replace `pandas.compat.scipy.scoreatpercentile` with `numpy.percentile` (GH6810)
- `.quantile` on a `datetime[ns]` series now returns `Timestamp` instead of `np.datetime64` objects (GH6810)
- change `AssertionError` to `TypeError` for invalid types passed to `concat` (GH6583)
- Raise a `TypeError` when `DataFrame` is passed an iterator as the `data` argument (GH5357)

Display changes

- The default way of printing large DataFrames has changed. DataFrames exceeding `max_rows` and/or `max_columns` are now displayed in a centrally truncated view, consistent with the printing of a *`pandas.Series`* (GH5603).

  In previous versions, a DataFrame was truncated once the dimension constraints were reached and an ellipse (...) signaled that part of the data was cut off.

```
In [1]: import pandas as pd

In [2]: import numpy as np

In [3]: pd.options.display.max_rows = 6

In [4]: pd.options.display.max_columns = 6

In [5]: index = pd.DatetimeIndex(start='20010101',freq='D',periods=10)

In [6]: pd.DataFrame(np.arange(10*10).reshape((10,10)),index=index)
Out[6]:
             0   1   2   3   4   5
2001-01-01   0   1   2   3   4   5 ...
2001-01-02  10  11  12  13  14  15 ...
2001-01-03  20  21  22  23  24  25 ...
2001-01-04  30  31  32  33  34  35 ...
2001-01-05  40  41  42  43  44  45 ...
2001-01-06  50  51  52  53  54  55 ...
           ... ... ... ... ... ...

[10 rows x 10 columns]
```

In the current version, large DataFrames are centrally truncated, showing a preview of head and tail in both dimensions.

```
In [24]: pd.DataFrame(np.arange(10*10).reshape((10,10)),index=index)
Out[24]:
              0   1   2 ...   7   8   9
2001-01-01    0   1   2 ...   7   8   9
2001-01-02   10  11  12 ...  17  18  19
2001-01-03   20  21  22 ...  27  28  29
...          ..  ..  .. ...  ..  ..  ..
2001-01-08   70  71  72 ...  77  78  79
2001-01-09   80  81  82 ...  87  88  89
2001-01-10   90  91  92 ...  97  98  99

[10 rows x 10 columns]
```

- allow option `'truncate'` for `display.show_dimensions` to only show the dimensions if the frame is truncated (GH6547).

  The default for `display.show_dimensions` will now be `truncate`. This is consistent with how Series display length.

```
In [16]: dfd = pd.DataFrame(np.arange(25).reshape(-1, 5),
   ....:                    index=[0, 1, 2, 3, 4],
   ....:                    columns=[0, 1, 2, 3, 4])
   ....:

# show dimensions since this is truncated
In [17]: with pd.option_context('display.max_rows', 2, 'display.max_columns', 2,
   ....:                        'display.show_dimensions', 'truncate'):
   ....:     print(dfd)
   ....:
     0  ...   4
0    0  ...   4
..  ..  ...  ..
4   20  ...  24

[5 rows x 5 columns]

# will not show dimensions since it is not truncated
In [18]: with pd.option_context('display.max_rows', 10, 'display.max_columns', 40,
   ....:                        'display.show_dimensions', 'truncate'):
   ....:     print(dfd)
   ....:
    0   1   2   3   4
0   0   1   2   3   4
1   5   6   7   8   9
2  10  11  12  13  14
3  15  16  17  18  19
4  20  21  22  23  24
```

- Regression in the display of a MultiIndexed Series with `display.max_rows` is less than the length of the series (GH7101)
- Fixed a bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the `large_repr` set to 'info' (GH7105)

- The `verbose` keyword in `DataFrame.info()`, which controls whether to shorten the `info` representation, is now `None` by default. This will follow the global setting in `display.max_info_columns`. The global setting can be overridden with `verbose=True` or `verbose=False`.
- Fixed a bug with the `info` repr not honoring the `display.max_info_columns` setting (GH6939)
- Offset/freq info now in Timestamp __repr__ (GH4553)

Text parsing API changes

read_csv()/*read_table()* will now be noisier w.r.t invalid options rather than falling back to the `PythonParser`.

- Raise `ValueError` when `sep` specified with `delim_whitespace=True` in *read_csv()*/*read_table()* (GH6607)
- Raise `ValueError` when `engine='c'` specified with unsupported options in *read_csv()*/*read_table()* (GH6607)
- Raise `ValueError` when fallback to python parser causes options to be ignored (GH6607)
- Produce `ParserWarning` on fallback to python parser when no options are ignored (GH6607)
- Translate `sep='\s+'` to `delim_whitespace=True` in *read_csv()*/*read_table()* if no other C-unsupported options specified (GH6607)

GroupBy API changes

More consistent behavior for some groupby methods:

- groupby `head` and `tail` now act more like `filter` rather than an aggregation:

```
In [19]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [20]: g = df.groupby('A')

In [21]: g.head(1)  # filters DataFrame
Out[21]:
   A  B
0  1  2
2  5  6

[2 rows x 2 columns]

In [22]: g.apply(lambda x: x.head(1))  # used to simply fall-through
Out[22]:
     A  B
A
1 0  1  2
5 2  5  6

[2 rows x 2 columns]
```

- groupby head and tail respect column selection:

```
In [23]: g[['B']].head(1)
Out[23]:
   B
```

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```
0  2
2  6

[2 rows x 1 columns]
```

- groupby `nth` now reduces by default; filtering can be achieved by passing `as_index=False`. With an optional `dropna` argument to ignore NaN. See *the docs*.

  Reducing

```
In [24]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [25]: g = df.groupby('A')

In [26]: g.nth(0)
Out[26]:
     B
A
1  NaN
5  6.0

[2 rows x 1 columns]

# this is equivalent to g.first()
In [27]: g.nth(0, dropna='any')
Out[27]:
     B
A
1  4.0
5  6.0

[2 rows x 1 columns]

# this is equivalent to g.last()
In [28]: g.nth(-1, dropna='any')
Out[28]:
     B
A
1  4.0
5  6.0

[2 rows x 1 columns]
```

  Filtering

```
In [29]: gf = df.groupby('A', as_index=False)

In [30]: gf.nth(0)
Out[30]:
   A    B
0  1  NaN
2  5  6.0

[2 rows x 2 columns]

In [31]: gf.nth(0, dropna='any')
Out[31]:
```

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```
   A    B
A
1  1  4.0
5  5  6.0

[2 rows x 2 columns]
```

- groupby will now not return the grouped column for non-cython functions (GH5610, GH5614, GH6732), as its already the index

```
In [32]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B
↪'])

In [33]: g = df.groupby('A')

In [34]: g.count()
Out[34]:
   B
A
1  1
5  2

[2 rows x 1 columns]

In [35]: g.describe()
Out[35]:
      B
  count mean       std  min  25%  50%  75%  max
A
1   1.0  4.0       NaN  4.0  4.0  4.0  4.0  4.0
5   2.0  7.0  1.414214  6.0  6.5  7.0  7.5  8.0

[2 rows x 8 columns]
```

- passing `as_index` will leave the grouped column in-place (this is not change in 0.14.0)

```
In [36]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B
↪'])

In [37]: g = df.groupby('A', as_index=False)

In [38]: g.count()
Out[38]:
   A  B
0  1  1
1  5  2

[2 rows x 2 columns]

In [39]: g.describe()
Out[39]:
      A                                     B                                    ␣
↪
  count mean  std  min  25%  50%  75%  max count mean       std  min  25%  50%  75
↪%  max
0   2.0  1.0  0.0  1.0  1.0  1.0  1.0  1.0   1.0  4.0       NaN  4.0  4.0  4.0  4.
↪0  4.0
```

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```
1   2.0  5.0  0.0  5.0  5.0  5.0  5.0  5.0   2.0  7.0  1.414214  6.0  6.5  7.0  7.
↪5  8.0

[2 rows x 16 columns]
```

- Allow specification of a more complex groupby via `pd.Grouper`, such as grouping by a Time and a string field simultaneously. See *the docs*. (GH3794)
- Better propagation/preservation of Series names when performing groupby operations:
  - `SeriesGroupBy.agg` will ensure that the name attribute of the original series is propagated to the result (GH6265).
  - If the function provided to `GroupBy.apply` returns a named series, the name of the series will be kept as the name of the column index of the DataFrame returned by `GroupBy.apply` (GH6124). This facilitates `DataFrame.stack` operations where the name of the column index is used as the name of the inserted column containing the pivoted data.

SQL

The SQL reading and writing functions now support more database flavors through SQLAlchemy (GH2717, GH4163, GH5950, GH6292). All databases supported by SQLAlchemy can be used, such as PostgreSQL, MySQL, Oracle, Microsoft SQL server (see documentation of SQLAlchemy on included dialects).

The functionality of providing DBAPI connection objects will only be supported for sqlite3 in the future. The `'mysql'` flavor is deprecated.

The new functions *`read_sql_query()`* and *`read_sql_table()`* are introduced. The function *`read_sql()`* is kept as a convenience wrapper around the other two and will delegate to specific function depending on the provided input (database table name or sql query).

In practice, you have to provide a SQLAlchemy `engine` to the sql functions. To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For an in-memory sqlite database:

```
In [40]: from sqlalchemy import create_engine

# Create your connection.
In [41]: engine = create_engine('sqlite:///:memory:')
```

This `engine` can then be used to write or read data to/from this database:

```
In [42]: df = pd.DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'c']})

In [43]: df.to_sql('db_table', engine, index=False)
```

You can read data from a database by specifying the table name:

```
In [44]: pd.read_sql_table('db_table', engine)
Out[44]:
   A  B
0  1  a
1  2  b
2  3  c

[3 rows x 2 columns]
```

or by specifying a sql query:

```
In [45]: pd.read_sql_query('SELECT * FROM db_table', engine)
Out[45]:
   A  B
0  1  a
1  2  b
2  3  c

[3 rows x 2 columns]
```

Some other enhancements to the sql functions include:

- support for writing the index. This can be controlled with the `index` keyword (default is True).
- specify the column label to use when writing the index with `index_label`.
- specify string columns to parse as datetimes with the `parse_dates` keyword in *`read_sql_query()`* and *`read_sql_table()`*.

Warning: Some of the existing functions or function aliases have been deprecated and will be removed in future versions. This includes: `tquery`, `uquery`, `read_frame`, `frame_query`, `write_frame`.

Warning: The support for the 'mysql' flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines (GH6900).

Multi-indexing using slicers

In 0.14.0 we added a new way to slice MultiIndexed objects. You can slice a MultiIndex by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see *Selection by Label*, including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of *that* level. You do not need to specify all the *deeper* levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

See *the docs* See also issues (GH6134, GH4036, GH3057, GH2598, GH5641, GH7106)

Warning:

You should specify all axes in the `.loc` specifier, meaning the indexer for the **index** and for the **columns**. Their are some ambiguous cases where the passed indexer could be mis-interpreted as indexing *both* axes, rather than into say the MuliIndex for the rows.

You should do this:

```
  >>> df.loc[(slice('A1', 'A3'), ...), :]  # noqa: E901

rather than this:
```

```
>>> df.loc[(slice('A1', 'A3'), ...)]  # noqa: E901
```

Warning: You will need to make sure that the selection axes are fully lexsorted!

```
In [46]: def mklbl(prefix, n):
   ....:     return ["%s%s" % (prefix, i) for i in range(n)]
   ....:

In [47]: index = pd.MultiIndex.from_product([mklbl('A', 4),
   ....:                                     mklbl('B', 2),
   ....:                                     mklbl('C', 4),
   ....:                                     mklbl('D', 2)])
   ....:

In [48]: columns = pd.MultiIndex.from_tuples([('a', 'foo'), ('a', 'bar'),
   ....:                                      ('b', 'foo'), ('b', 'bah')],
   ....:                                     names=['lvl0', 'lvl1'])
   ....:

In [49]: df = pd.DataFrame(np.arange(len(index) * len(columns)).reshape((len(index),
   ....:                   len(columns))),
   ....:                   index=index,
   ....:                   columns=columns).sort_index().sort_index(axis=1)
   ....:

In [50]: df
Out[50]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
         D1    5    4    7    6
      C1 D0    9    8   11   10
         D1   13   12   15   14
      C2 D0   17   16   19   18
...          ...  ...  ...  ...
A3 B1 C1 D1  237  236  239  238
      C2 D0  241  240  243  242
         D1  245  244  247  246
      C3 D0  249  248  251  250
         D1  253  252  255  254

[64 rows x 4 columns]
```

Basic MultiIndex slicing using slices, lists, and labels.

```
In [51]: df.loc[(slice('A1', 'A3'), slice(None), ['C1', 'C3']), :]
Out[51]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A1 B0 C1 D0   73   72   75   74
         D1   77   76   79   78
      C3 D0   89   88   91   90
         D1   93   92   95   94
   B1 C1 D0  105  104  107  106
...          ...  ...  ...  ...
A3 B0 C3 D1  221  220  223  222
   B1 C1 D0  233  232  235  234
         D1  237  236  239  238
```

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```
      C3 D0  249  248  251  250
         D1  253  252  255  254

[24 rows x 4 columns]
```

You can use a `pd.IndexSlice` to shortcut the creation of these slices

```
In [52]: idx = pd.IndexSlice

In [53]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out[53]:
lvl0           a    b
lvl1         foo  foo
A0 B0 C1 D0    8   10
         D1   12   14
      C3 D0   24   26
         D1   28   30
   B1 C1 D0   40   42
...          ...  ...
A3 B0 C3 D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254

[32 rows x 2 columns]
```

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```
In [54]: df.loc['A1', (slice(None), 'foo')]
Out[54]:
lvl0        a    b
lvl1      foo  foo
B0 C0 D0   64   66
      D1   68   70
   C1 D0   72   74
      D1   76   78
   C2 D0   80   82
...       ...  ...
B1 C1 D1  108  110
   C2 D0  112  114
      D1  116  118
   C3 D0  120  122
      D1  124  126

[16 rows x 2 columns]

In [55]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out[55]:
lvl0           a    b
lvl1         foo  foo
A0 B0 C1 D0    8   10
         D1   12   14
      C3 D0   24   26
         D1   28   30
   B1 C1 D0   40   42
...          ...  ...
```

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```
A3 B0 C3 D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254

[32 rows x 2 columns]
```

Using a boolean indexer you can provide selection related to the *values*.

```
In [56]: mask = df[('a', 'foo')] > 200

In [57]: df.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]
Out[57]:
lvl0           a    b
lvl1         foo  foo
A3 B0 C1 D1  204  206
      C3 D0  216  218
         D1  220  222
   B1 C1 D0  232  234
         D1  236  238
      C3 D0  248  250
         D1  252  254

[7 rows x 2 columns]
```

You can also specify the `axis` argument to `.loc` to interpret the passed slicers on a single axis.

```
In [58]: df.loc(axis=0)[:, :, ['C1', 'C3']]
Out[58]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C1 D0    9    8   11   10
         D1   13   12   15   14
      C3 D0   25   24   27   26
         D1   29   28   31   30
   B1 C1 D0   41   40   43   42
...          ...  ...  ...  ...
A3 B0 C3 D1  221  220  223  222
   B1 C1 D0  233  232  235  234
         D1  237  236  239  238
      C3 D0  249  248  251  250
         D1  253  252  255  254

[32 rows x 4 columns]
```

Furthermore you can *set* the values using these methods

```
In [59]: df2 = df.copy()

In [60]: df2.loc(axis=0)[:, :, ['C1', 'C3']] = -10

In [61]: df2
Out[61]:
lvl0           a         b
lvl1         bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
```

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```
          D1    5    4    7    6
      C1 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10
      C2 D0   17   16   19   18
...          ...  ...  ...  ...
A3 B1 C1 D1  -10  -10  -10  -10
      C2 D0  241  240  243  242
         D1  245  244  247  246
      C3 D0  -10  -10  -10  -10
         D1  -10  -10  -10  -10

[64 rows x 4 columns]
```

You can use a right-hand-side of an alignable object as well.

```
In [62]: df2 = df.copy()

In [63]: df2.loc[idx[:, :, ['C1', 'C3']], :] = df2 * 1000

In [64]: df2
Out[64]:
lvl0              a               b
lvl1            bar     foo     bah     foo
A0 B0 C0 D0       1       0       3       2
         D1       5       4       7       6
      C1 D0    9000    8000   11000   10000
         D1   13000   12000   15000   14000
      C2 D0      17      16      19      18
...             ...     ...     ...     ...
A3 B1 C1 D1  237000  236000  239000  238000
      C2 D0     241     240     243     242
         D1     245     244     247     246
      C3 D0  249000  248000  251000  250000
         D1  253000  252000  255000  254000

[64 rows x 4 columns]
```

Plotting

- Hexagonal bin plots from `DataFrame.plot` with `kind='hexbin'` (GH5478), See *the docs*.
- `DataFrame.plot` and `Series.plot` now supports area plot with specifying `kind='area'` (GH6656), See *the docs*
- Pie plots from `Series.plot` and `DataFrame.plot` with `kind='pie'` (GH6976), See *the docs*.
- Plotting with Error Bars is now supported in the `.plot` method of `DataFrame` and `Series` objects (GH3796, GH6834), See *the docs*.
- `DataFrame.plot` and `Series.plot` now support a `table` keyword for plotting `matplotlib.Table`, See *the docs*. The `table` keyword can receive the following values.
  - `False`: Do nothing (default).
  - `True`: Draw a table using the `DataFrame` or `Series` called `plot` method. Data will be transposed to meet matplotlib's default layout.

  - `DataFrame` or `Series`: Draw matplotlib.table using the passed data. The data will be drawn as displayed in print method (not transposed automatically). Also, helper function `pandas.tools.plotting.table` is added to create a table from `DataFrame` and `Series`, and add it to an `matplotlib.Axes`.

- `plot(legend='reverse')` will now reverse the order of legend labels for most plot kinds. (GH6014)
- Line plot and area plot can be stacked by `stacked=True` (GH6656)
- Following keywords are now acceptable for *`DataFrame.plot()`* with `kind='bar'` and `kind='barh'`:
  - `width`: Specify the bar width. In previous versions, static value 0.5 was passed to matplotlib and it cannot be overwritten. (GH6604)
  - `align`: Specify the bar alignment. Default is `center` (different from matplotlib). In previous versions, pandas passes `align='edge'` to matplotlib and adjust the location to `center` by itself, and it results `align` keyword is not applied as expected. (GH4525)
  - `position`: Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1(right/top-end). Default is 0.5 (center). (GH6604)

  Because of the default `align` value changes, coordinates of bar plots are now located on integer values (0.0, 1.0, 2.0 . . .). This is intended to make bar plot be located on the same coordinates as line plot. However, bar plot may differs unexpectedly when you manually adjust the bar location or drawing area, such as using `set_xlim`, `set_ylim`, etc. In this cases, please modify your script to meet with new coordinates.
- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A `FutureWarning` is raised to alert that the old `colors` argument will not be supported in a future release. (GH6956)
- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A `FutureWarning` is raised if the old `data` argument is used by name. (GH6956)
- *`DataFrame.boxplot()`* now supports `layout` keyword (GH6769)
- *`DataFrame.boxplot()`* has a new keyword argument, `return_type`. It accepts `'dict'`, `'axes'`, or `'both'`, in which case a namedtuple with the matplotlib axes and a dict of matplotlib Lines is returned.

Prior version deprecations/changes

There are prior version deprecations that are taking effect as of 0.14.0.

- Remove `DateRange` in favor of *`DatetimeIndex`* (GH6816)
- Remove `column` keyword from `DataFrame.sort` (GH4370)
- Remove `precision` keyword from `set_eng_float_format()` (GH395)
- Remove `force_unicode` keyword from *`DataFrame.to_string()`*, *`DataFrame.to_latex()`*, and *`DataFrame.to_html()`*; these function encode in unicode by default (GH2224, GH2225)
- Remove `nanRep` keyword from *`DataFrame.to_csv()`* and *`DataFrame.to_string()`* (GH275)
- Remove `unique` keyword from `HDFStore.select_column()` (GH3256)
- Remove `inferTimeRule` keyword from `Timestamp.offset()` (GH391)
- Remove `name` keyword from `get_data_yahoo()` and `get_data_google()` (commit b921d1a)
- Remove `offset` keyword from *`DatetimeIndex`* constructor (commit 3136390)
- Remove `time_rule` from several rolling-moment statistical functions, such as `rolling_sum()` (GH1042)

- Removed neg – boolean operations on numpy arrays in favor of inv ~, as this is going to be deprecated in numpy 1.9 (GH6960)

Deprecations

- The *pivot_table()*/*DataFrame.pivot_table()* and *crosstab()* functions now take arguments `index` and `columns` instead of `rows` and `cols`. A `FutureWarning` is raised to alert that the old `rows` and `cols` arguments will not be supported in a future release (GH5505)
- The *DataFrame.drop_duplicates()* and *DataFrame.duplicated()* methods now take argument `subset` instead of `cols` to better align with *DataFrame.dropna()*. A `FutureWarning` is raised to alert that the old `cols` arguments will not be supported in a future release (GH6680)
- The *DataFrame.to_csv()* and *DataFrame.to_excel()* functions now takes argument `columns` instead of `cols`. A `FutureWarning` is raised to alert that the old `cols` arguments will not be supported in a future release (GH6645)
- Indexers will warn `FutureWarning` when used with a scalar indexer and a non-floating point Index (GH4892, GH6960)

```
# non-floating point indexes can only be indexed by integers / labels
In [1]: pd.Series(1, np.arange(5))[3.0]
        pandas/core/index.py:469: FutureWarning: scalar indexers for index type␣
↪Int64Index should be integers and not floating point
Out[1]: 1

In [2]: pd.Series(1, np.arange(5)).iloc[3.0]
        pandas/core/index.py:469: FutureWarning: scalar indexers for index type␣
↪Int64Index should be integers and not floating point
Out[2]: 1

In [3]: pd.Series(1, np.arange(5)).iloc[3.0:4]
        pandas/core/index.py:527: FutureWarning: slice indexers when using iloc␣
↪should be integers and not floating point
Out[3]:
        3    1
        dtype: int64

# these are Float64Indexes, so integer or floating point is acceptable
In [4]: pd.Series(1, np.arange(5.))[3]
Out[4]: 1

In [5]: pd.Series(1, np.arange(5.))[3.0]
Out[6]: 1
```

- Numpy 1.9 compat w.r.t. deprecation warnings (GH6960)
- `Panel.shift()` now has a function signature that matches *DataFrame.shift()*. The old positional argument `lags` has been changed to a keyword argument `periods` with a default value of 1. A `FutureWarning` is raised if the old argument `lags` is used by name. (GH6910)
- The `order` keyword argument of *factorize()* will be removed. (GH6926).
- Remove the `copy` keyword from *DataFrame.xs()*, `Panel.major_xs()`, `Panel.minor_xs()`. A view will be returned if possible, otherwise a copy will be made. Previously the user could think that `copy=False` would ALWAYS return a view. (GH6894)
- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A `FutureWarning` is raised to alert that the old `colors` argument will not be supported in a future release.

(GH6956)

- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A `FutureWarning` is raised if the old `data` argument is used by name. (GH6956)
- The support for the 'mysql' flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines (GH6900).
- The following `io.sql` functions have been deprecated: `tquery`, `uquery`, `read_frame`, `frame_query`, `write_frame`.
- The `percentile_width` keyword argument in *`describe()`* has been deprecated. Use the `percentiles` keyword instead, which takes a list of percentiles to display. The default output is unchanged.
- The default return type of `boxplot()` will change from a dict to a matplotlib Axes in a future release. You can use the future behavior now by passing `return_type='axes'` to boxplot.

Known issues

- OpenPyXL 2.0.0 breaks backwards compatibility (GH7169)

Enhancements

- DataFrame and Series will create a MultiIndex object if passed a tuples dict, See *the docs* (GH3323)

```
In [65]: pd.Series({('a', 'b'): 1, ('a', 'a'): 0,
   ....:            ('a', 'c'): 2, ('b', 'a'): 3, ('b', 'b'): 4})
   ....:
Out[65]:
a  b    1
   a    0
   c    2
b  a    3
   b    4
Length: 5, dtype: int64

In [66]: pd.DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
   ....:               ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
   ....:               ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},
   ....:               ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},
   ....:               ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})
   ....:
Out[66]:
       a              b
       b    a    c    a     b
A B  1.0  4.0  5.0  8.0  10.0
  C  2.0  3.0  6.0  7.0   NaN
  D  NaN  NaN  NaN  NaN   9.0

[3 rows x 5 columns]
```

- Added the `sym_diff` method to `Index` (GH5543)
- `DataFrame.to_latex` now takes a longtable keyword, which if True will return a table in a longtable environment. (GH6617)
- Add option to turn off escaping in `DataFrame.to_latex` (GH6472)

- `pd.read_clipboard` will, if the keyword `sep` is unspecified, try to detect data copied from a spreadsheet and parse accordingly. (GH6223)
- Joining a singly-indexed DataFrame with a MultiIndexed DataFrame (GH3662)

  See *the docs*. Joining MultiIndex DataFrames on both the left and right is not yet supported ATM.

```
In [67]: household = pd.DataFrame({'household_id': [1, 2, 3],
   ....:                           'male': [0, 1, 0],
   ....:                           'wealth': [196087.3, 316478.7, 294750]
   ....:                           },
   ....:                          columns=['household_id', 'male', 'wealth']
   ....:                          ).set_index('household_id')
   ....:

In [68]: household
Out[68]:
              male    wealth
household_id
1                0  196087.3
2                1  316478.7
3                0  294750.0

[3 rows x 2 columns]

In [69]: portfolio = pd.DataFrame({'household_id': [1, 2, 2, 3, 3, 3, 4],
   ....:                           'asset_id': ["nl0000301109",
   ....:                                        "nl0000289783",
   ....:                                        "gb00b03mlx29",
   ....:                                        "gb00b03mlx29",
   ....:                                        "lu0197800237",
   ....:                                        "nl0000289965",
   ....:                                        np.nan],
   ....:                           'name': ["ABN Amro",
   ....:                                    "Robeco",
   ....:                                    "Royal Dutch Shell",
   ....:                                    "Royal Dutch Shell",
   ....:                                    "AAB Eastern Europe Equity Fund",
   ....:                                    "Postbank BioTech Fonds",
   ....:                                    np.nan],
   ....:                           'share': [1.0, 0.4, 0.6, 0.15, 0.6, 0.25, 1.0]
   ....:                           },
   ....:                          columns=['household_id', 'asset_id', 'name',
↪'share']
   ....:                          ).set_index(['household_id', 'asset_id'])
   ....:

In [70]: portfolio
Out[70]:
                                                 name  share
household_id asset_id
1            nl0000301109                     ABN Amro   1.00
2            nl0000289783                       Robeco   0.40
             gb00b03mlx29              Royal Dutch Shell   0.60
3            gb00b03mlx29              Royal Dutch Shell   0.15
             lu0197800237  AAB Eastern Europe Equity Fund   0.60
             nl0000289965          Postbank BioTech Fonds   0.25
4            NaN                                     NaN   1.00
```

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```
[7 rows x 2 columns]

In [71]: household.join(portfolio, how='inner')
Out[71]:
                          male    wealth                             name  share
household_id asset_id
1            nl0000301109     0  196087.3                         ABN Amro   1.00
2            nl0000289783     1  316478.7                           Robeco   0.40
             gb00b03mlx29     1  316478.7                Royal Dutch Shell   0.60
3            gb00b03mlx29     0  294750.0                Royal Dutch Shell   0.15
             lu0197800237     0  294750.0  AAB Eastern Europe Equity Fund   0.60
             nl0000289965     0  294750.0           Postbank BioTech Fonds   0.25

[6 rows x 4 columns]
```

- `quotechar`, `doublequote`, and `escapechar` can now be specified when using `DataFrame.to_csv` (GH5414, GH4528)
- Partially sort by only the specified levels of a MultiIndex with the `sort_remaining` boolean kwarg. (GH3984)
- Added `to_julian_date` to `TimeStamp` and `DatetimeIndex`. The Julian Date is used primarily in astronomy and represents the number of days from noon, January 1, 4713 BC. Because nanoseconds are used to define the time in pandas the actual range of dates that you can use is 1678 AD to 2262 AD. (GH4041)
- `DataFrame.to_stata` will now check data for compatibility with Stata data types and will upcast when needed. When it is not possible to losslessly upcast, a warning is issued (GH6327)
- `DataFrame.to_stata` and `StataWriter` will accept keyword arguments time_stamp and data_label which allow the time stamp and dataset label to be set when creating a file. (GH6545)
- `pandas.io.gbq` now handles reading unicode strings properly. (GH5940)
- *Holidays Calendars* are now available and can be used with the `CustomBusinessDay` offset (GH6719)
- `Float64Index` is now backed by a `float64` dtype ndarray instead of an `object` dtype array (GH6471).
- Implemented `Panel.pct_change` (GH6904)
- Added `how` option to rolling-moment functions to dictate how to handle resampling; `rolling_max()` defaults to max, `rolling_min()` defaults to min, and all others default to mean (GH6297)
- `CustomBusinessMonthBegin` and `CustomBusinessMonthEnd` are now available (GH6866)
- *`Series.quantile()`* and *`DataFrame.quantile()`* now accept an array of quantiles.
- *`describe()`* now accepts an array of percentiles to include in the summary statistics (GH4196)
- `pivot_table` can now accept `Grouper` by `index` and `columns` keywords (GH6913)

```
In [72]: import datetime

In [73]: df = pd.DataFrame({
   ....:     'Branch': 'A A A A A B'.split(),
   ....:     'Buyer': 'Carl Mark Carl Carl Joe Joe'.split(),
   ....:     'Quantity': [1, 3, 5, 1, 8, 1],
   ....:     'Date': [datetime.datetime(2013, 11, 1, 13, 0),
   ....:              datetime.datetime(2013, 9, 1, 13, 5),
   ....:              datetime.datetime(2013, 10, 1, 20, 0),
   ....:              datetime.datetime(2013, 10, 2, 10, 0),
   ....:              datetime.datetime(2013, 11, 1, 20, 0),
```

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```
   ....:                datetime.datetime(2013, 10, 2, 10, 0)],
   ....:      'PayDay': [datetime.datetime(2013, 10, 4, 0, 0),
   ....:                 datetime.datetime(2013, 10, 15, 13, 5),
   ....:                 datetime.datetime(2013, 9, 5, 20, 0),
   ....:                 datetime.datetime(2013, 11, 2, 10, 0),
   ....:                 datetime.datetime(2013, 10, 7, 20, 0),
   ....:                 datetime.datetime(2013, 9, 5, 10, 0)]})
   ....:

In [74]: df
Out[74]:
  Branch Buyer  Quantity                Date              PayDay
0      A  Carl         1 2013-11-01 13:00:00 2013-10-04 00:00:00
1      A  Mark         3 2013-09-01 13:05:00 2013-10-15 13:05:00
2      A  Carl         5 2013-10-01 20:00:00 2013-09-05 20:00:00
3      A  Carl         1 2013-10-02 10:00:00 2013-11-02 10:00:00
4      A   Joe         8 2013-11-01 20:00:00 2013-10-07 20:00:00
5      B   Joe         1 2013-10-02 10:00:00 2013-09-05 10:00:00

[6 rows x 5 columns]

In [75]: df.pivot_table(values='Quantity',
   ....:                index=pd.Grouper(freq='M', key='Date'),
   ....:                columns=pd.Grouper(freq='M', key='PayDay'),
   ....:                aggfunc=np.sum)
   ....:
Out[75]:
PayDay      2013-09-30  2013-10-31  2013-11-30
Date
2013-09-30         NaN         3.0         NaN
2013-10-31         6.0         NaN         1.0
2013-11-30         NaN         9.0         NaN

[3 rows x 3 columns]
```

- Arrays of strings can be wrapped to a specified width (`str.wrap`) (GH6999)
- Add *`nsmallest()`* and *`Series.nlargest()`* methods to Series, See *the docs* (GH3960)
- `PeriodIndex` fully supports partial string indexing like `DatetimeIndex` (GH7043)

```
In [76]: prng = pd.period_range('2013-01-01 09:00', periods=100, freq='H')

In [77]: ps = pd.Series(np.random.randn(len(prng)), index=prng)

In [78]: ps
Out[78]:
2013-01-01 09:00    0.015696
2013-01-01 10:00   -2.242685
2013-01-01 11:00    1.150036
2013-01-01 12:00    0.991946
2013-01-01 13:00    0.953324
                      ...
2013-01-05 08:00    0.285296
2013-01-05 09:00    0.484288
2013-01-05 10:00    1.363482
2013-01-05 11:00   -0.781105
```

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```
2013-01-05 12:00   -0.468018
Freq: H, Length: 100, dtype: float64

In [79]: ps['2013-01-02']
Out[79]:
2013-01-02 00:00    0.553439
2013-01-02 01:00    1.318152
2013-01-02 02:00   -0.469305
2013-01-02 03:00    0.675554
2013-01-02 04:00   -1.817027
                      ...
2013-01-02 19:00    0.036142
2013-01-02 20:00   -2.074978
2013-01-02 21:00    0.247792
2013-01-02 22:00   -0.897157
2013-01-02 23:00   -0.136795
Freq: H, Length: 24, dtype: float64
```

- `read_excel` can now read milliseconds in Excel dates and times with xlrd >= 0.9.3. (GH5945)
- `pd.stats.moments.rolling_var` now uses Welford's method for increased numerical stability (GH6817)
- pd.expanding_apply and pd.rolling_apply now take args and kwargs that are passed on to the func (GH6289)
- `DataFrame.rank()` now has a percentage rank option (GH5971)
- `Series.rank()` now has a percentage rank option (GH5971)
- `Series.rank()` and `DataFrame.rank()` now accept `method='dense'` for ranks without gaps (GH6514)
- Support passing `encoding` with xlwt (GH3710)
- Refactor Block classes removing `Block.items` attributes to avoid duplication in item handling (GH6745, GH6988).
- Testing statements updated to use specialized asserts (GH6175)

Performance

- Performance improvement when converting `DatetimeIndex` to floating ordinals using `DatetimeConverter` (GH6636)
- Performance improvement for `DataFrame.shift` (GH5609)
- Performance improvement in indexing into a MultiIndexed Series (GH5567)
- Performance improvements in single-dtyped indexing (GH6484)
- Improve performance of DataFrame construction with certain offsets, by removing faulty caching (e.g. MonthEnd,BusinessMonthEnd), (GH6479)
- Improve performance of `CustomBusinessDay` (GH6584)
- improve performance of slice indexing on Series with string keys (GH6341, GH6372)
- Performance improvement for `DataFrame.from_records` when reading a specified number of rows from an iterable (GH6700)
- Performance improvements in timedelta conversions for integer dtypes (GH6754)

- Improved performance of compatible pickles (GH6899)
- Improve performance in certain reindexing operations by optimizing `take_2d` (GH6749)
- `GroupBy.count()` is now implemented in Cython and is much faster for large numbers of groups (GH7016).

Experimental

There are no experimental changes in 0.14.0

Bug fixes

- Bug in Series ValueError when index doesn't match data (GH6532)
- Prevent segfault due to MultiIndex not being supported in HDFStore table format (GH1848)
- Bug in `pd.DataFrame.sort_index` where mergesort wasn't stable when `ascending=False` (GH6399)
- Bug in `pd.tseries.frequencies.to_offset` when argument has leading zeros (GH6391)
- Bug in version string gen. for dev versions with shallow clones / install from tarball (GH6127)
- Inconsistent tz parsing `Timestamp` / `to_datetime` for current year (GH5958)
- Indexing bugs with reordered indexes (GH6252, GH6254)
- Bug in `.xs` with a Series multiindex (GH6258, GH5684)
- Bug in conversion of a string types to a DatetimeIndex with a specified frequency (GH6273, GH6274)
- Bug in `eval` where type-promotion failed for large expressions (GH6205)
- Bug in interpolate with `inplace=True` (GH6281)
- `HDFStore.remove` now handles start and stop (GH6177)
- `HDFStore.select_as_multiple` handles start and stop the same way as `select` (GH6177)
- `HDFStore.select_as_coordinates` and `select_column` works with a `where` clause that results in filters (GH6177)
- Regression in join of non_unique_indexes (GH6329)
- Issue with groupby `agg` with a single function and a mixed-type frame (GH6337)
- Bug in `DataFrame.replace()` when passing a non- `bool` `to_replace` argument (GH6332)
- Raise when trying to align on different levels of a MultiIndex assignment (GH3738)
- Bug in setting complex dtypes via boolean indexing (GH6345)
- Bug in TimeGrouper/resample when presented with a non-monotonic DatetimeIndex that would return invalid results. (GH4161)
- Bug in index name propagation in TimeGrouper/resample (GH4161)
- TimeGrouper has a more compatible API to the rest of the groupers (e.g. `groups` was missing) (GH3881)
- Bug in multiple grouping with a TimeGrouper depending on target column order (GH6764)
- Bug in `pd.eval` when parsing strings with possible tokens like `'&'` (GH6351)
- Bug correctly handle placements of `-inf` in Panels when dividing by integer 0 (GH6178)
- `DataFrame.shift` with `axis=1` was raising (GH6371)

- Disabled clipboard tests until release time (run locally with `nosetests -A disabled`) (GH6048).
- Bug in `DataFrame.replace()` when passing a nested `dict` that contained keys not in the values to be replaced (GH6342)
- `str.match` ignored the na flag (GH6609).
- Bug in take with duplicate columns that were not consolidated (GH6240)
- Bug in interpolate changing dtypes (GH6290)
- Bug in `Series.get`, was using a buggy access method (GH6383)
- Bug in hdfstore queries of the form `where=[('date', '>=', datetime(2013,1,1)), ('date', '<=', datetime(2014,1,1))]` (GH6313)
- Bug in `DataFrame.dropna` with duplicate indices (GH6355)
- Regression in chained getitem indexing with embedded list-like from 0.12 (GH6394)
- `Float64Index` with nans not comparing correctly (GH6401)
- `eval`/`query` expressions with strings containing the `@` character will now work (GH6366).
- Bug in `Series.reindex` when specifying a `method` with some nan values was inconsistent (noted on a resample) (GH6418)
- Bug in *`DataFrame.replace()`* where nested dicts were erroneously depending on the order of dictionary keys and values (GH5338).
- Performance issue in concatenating with empty objects (GH3259)
- Clarify sorting of `sym_diff` on `Index` objects with `NaN` values (GH6444)
- Regression in `MultiIndex.from_product` with a `DatetimeIndex` as input (GH6439)
- Bug in `str.extract` when passed a non-default index (GH6348)
- Bug in `str.split` when passed `pat=None` and `n=1` (GH6466)
- Bug in `io.data.DataReader` when passed `"F-F_Momentum_Factor"` and `data_source="famafrench"` (GH6460)
- Bug in `sum` of a `timedelta64[ns]` series (GH6462)
- Bug in `resample` with a timezone and certain offsets (GH6397)
- Bug in `iat/iloc` with duplicate indices on a Series (GH6493)
- Bug in `read_html` where nan's were incorrectly being used to indicate missing values in text. Should use the empty string for consistency with the rest of pandas (GH5129).
- Bug in `read_html` tests where redirected invalid URLs would make one test fail (GH6445).
- Bug in multi-axis indexing using `.loc` on non-unique indices (GH6504)
- Bug that caused _ref_locs corruption when slice indexing across columns axis of a DataFrame (GH6525)
- Regression from 0.13 in the treatment of numpy `datetime64` non-ns dtypes in Series creation (GH6529)
- `.names` attribute of MultiIndexes passed to `set_index` are now preserved (GH6459).
- Bug in setitem with a duplicate index and an alignable rhs (GH6541)
- Bug in setitem with `.loc` on mixed integer Indexes (GH6546)
- Bug in `pd.read_stata` which would use the wrong data types and missing values (GH6327)

- Bug in `DataFrame.to_stata` that lead to data loss in certain cases, and could be exported using the wrong data types and missing values (GH6335)
- `StataWriter` replaces missing values in string columns by empty string (GH6802)
- Inconsistent types in `Timestamp` addition/subtraction (GH6543)
- Bug in preserving frequency across Timestamp addition/subtraction (GH4547)
- Bug in empty list lookup caused `IndexError` exceptions (GH6536, GH6551)
- `Series.quantile` raising on an `object` dtype (GH6555)
- Bug in `.xs` with a `nan` in level when dropped (GH6574)
- Bug in fillna with `method='bfill/ffill'` and `datetime64[ns]` dtype (GH6587)
- Bug in sql writing with mixed dtypes possibly leading to data loss (GH6509)
- Bug in `Series.pop` (GH6600)
- Bug in `iloc` indexing when positional indexer matched `Int64Index` of the corresponding axis and no reordering happened (GH6612)
- Bug in `fillna` with `limit` and `value` specified
- Bug in `DataFrame.to_stata` when columns have non-string names (GH4558)
- Bug in compat with `np.compress`, surfaced in (GH6658)
- Bug in binary operations with a rhs of a Series not aligning (GH6681)
- Bug in `DataFrame.to_stata` which incorrectly handles nan values and ignores `with_index` keyword argument (GH6685)
- Bug in resample with extra bins when using an evenly divisible frequency (GH4076)
- Bug in consistency of groupby aggregation when passing a custom function (GH6715)
- Bug in resample when `how=None` resample freq is the same as the axis frequency (GH5955)
- Bug in downcasting inference with empty arrays (GH6733)
- Bug in `obj.blocks` on sparse containers dropping all but the last items of same for dtype (GH6748)
- Bug in unpickling `NaT (NaTType)` (GH4606)
- Bug in `DataFrame.replace()` where regex meta characters were being treated as regex even when `regex=False` (GH6777).
- Bug in timedelta ops on 32-bit platforms (GH6808)
- Bug in setting a tz-aware index directly via `.index` (GH6785)
- Bug in expressions.py where numexpr would try to evaluate arithmetic ops (GH6762).
- Bug in Makefile where it didn't remove Cython generated C files with `make clean` (GH6768)
- Bug with numpy < 1.7.2 when reading long strings from `HDFStore` (GH6166)
- Bug in `DataFrame._reduce` where non bool-like (0/1) integers were being converted into bools. (GH6806)
- Regression from 0.13 with `fillna` and a Series on datetime-like (GH6344)
- Bug in adding `np.timedelta64` to `DatetimeIndex` with timezone outputs incorrect results (GH6818)
- Bug in `DataFrame.replace()` where changing a dtype through replacement would only replace the first occurrence of a value (GH6689)
- Better error message when passing a frequency of 'MS' in `Period` construction (GH5332)

- Bug in `Series.__unicode__` when `max_rows=None` and the Series has more than 1000 rows. (GH6863)
- Bug in `groupby.get_group` where a datelike wasn't always accepted (GH5267)
- Bug in `groupBy.get_group` created by `TimeGrouper` raises `AttributeError` (GH6914)
- Bug in `DatetimeIndex.tz_localize` and `DatetimeIndex.tz_convert` converting `NaT` incorrectly (GH5546)
- Bug in arithmetic operations affecting `NaT` (GH6873)
- Bug in `Series.str.extract` where the resulting `Series` from a single group match wasn't renamed to the group name
- Bug in `DataFrame.to_csv` where setting `index=False` ignored the `header` kwarg (GH6186)
- Bug in `DataFrame.plot` and `Series.plot`, where the legend behave inconsistently when plotting to the same axes repeatedly (GH6678)
- Internal tests for patching `__finalize__` / bug in merge not finalizing (GH6923, GH6927)
- accept `TextFileReader` in `concat`, which was affecting a common user idiom (GH6583)
- Bug in C parser with leading white space (GH3374)
- Bug in C parser with `delim_whitespace=True` and `\r`-delimited lines
- Bug in python parser with explicit MultiIndex in row following column header (GH6893)
- Bug in `Series.rank` and `DataFrame.rank` that caused small floats (<1e-13) to all receive the same rank (GH6886)
- Bug in `DataFrame.apply` with functions that used `*args` or `**kwargs` and returned an empty result (GH6952)
- Bug in sum/mean on 32-bit platforms on overflows (GH6915)
- Moved `Panel.shift` to `NDFrame.slice_shift` and fixed to respect multiple dtypes. (GH6959)
- Bug in enabling `subplots=True` in `DataFrame.plot` only has single column raises `TypeError`, and `Series.plot` raises `AttributeError` (GH6951)
- Bug in `DataFrame.plot` draws unnecessary axes when enabling `subplots` and `kind=scatter` (GH6951)
- Bug in `read_csv` from a filesystem with non-utf-8 encoding (GH6807)
- Bug in `iloc` when setting / aligning (GH6766)
- Bug causing UnicodeEncodeError when get_dummies called with unicode values and a prefix (GH6885)
- Bug in timeseries-with-frequency plot cursor display (GH5453)
- Bug surfaced in `groupby.plot` when using a `Float64Index` (GH7025)
- Stopped tests from failing if options data isn't able to be downloaded from Yahoo (GH7034)
- Bug in `parallel_coordinates` and `radviz` where reordering of class column caused possible color/class mismatch (GH6956)
- Bug in `radviz` and `andrews_curves` where multiple values of 'color' were being passed to plotting method (GH6956)
- Bug in `Float64Index.isin()` where containing `nan`s would make indices claim that they contained all the things (GH7066).
- Bug in `DataFrame.boxplot` where it failed to use the axis passed as the `ax` argument (GH3578)

- Bug in the `XlsxWriter` and `XlwtWriter` implementations that resulted in datetime columns being formatted without the time (GH7075) were being passed to plotting method
- *`read_fwf()`* treats `None` in `colspec` like regular python slices. It now reads from the beginning or until the end of the line when `colspec` contains a `None` (previously raised a `TypeError`)
- Bug in cache coherence with chained indexing and slicing; add `_is_view` property to `NDFrame` to correctly predict views; mark `is_copy` on `xs` only if its an actual copy (and not a view) (GH7084)
- Bug in DatetimeIndex creation from string ndarray with `dayfirst=True` (GH5917)
- Bug in `MultiIndex.from_arrays` created from `DatetimeIndex` doesn't preserve `freq` and `tz` (GH7090)
- Bug in `unstack` raises `ValueError` when `MultiIndex` contains `PeriodIndex` (GH4342)
- Bug in `boxplot` and `hist` draws unnecessary axes (GH6769)
- Regression in `groupby.nth()` for out-of-bounds indexers (GH6621)
- Bug in `quantile` with datetime values (GH6965)
- Bug in `Dataframe.set_index`, `reindex` and `pivot` don't preserve `DatetimeIndex` and `PeriodIndex` attributes (GH3950, GH5878, GH6631)
- Bug in `MultiIndex.get_level_values` doesn't preserve `DatetimeIndex` and `PeriodIndex` attributes (GH7092)
- Bug in `Groupby` doesn't preserve `tz` (GH3950)
- Bug in `PeriodIndex` partial string slicing (GH6716)
- Bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the `large_repr` set to 'info' (GH7105)
- Bug in `DatetimeIndex` specifying `freq` raises `ValueError` when passed value is too short (GH7098)
- Fixed a bug with the `info` repr not honoring the `display.max_info_columns` setting (GH6939)
- Bug `PeriodIndex` string slicing with out of bounds values (GH5407)
- Fixed a memory error in the hashtable implementation/factorizer on resizing of large tables (GH7157)
- Bug in `isnull` when applied to 0-dimensional object arrays (GH7176)
- Bug in `query`/`eval` where global constants were not looked up correctly (GH7178)
- Bug in recognizing out-of-bounds positional list indexers with `iloc` and a multi-axis tuple indexer (GH7189)
- Bug in setitem with a single value, MultiIndex and integer indices (GH7190, GH7218)
- Bug in expressions evaluation with reversed ops, showing in series-dataframe ops (GH7198, GH7192)
- Bug in multi-axis indexing with > 2 ndim and a MultiIndex (GH7199)
- Fix a bug where invalid eval/query operations would blow the stack (GH5198)

Contributors

A total of 94 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- jaimefrio +
- jreback
- jsexauer +
- kdiether +
- michaelws +
- mikebailey +
- ojdo +
- onesandzeroes +
- phaebz +
- ribonoous +
- rockg
- sinhrks +
- unutbu
- westurner
- y-p
- zach powers

5.16 Version 0.13

5.16.1 Version 0.13.1 (February 3, 2014)

This is a minor release from 0.13.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Added `infer_datetime_format` keyword to `read_csv/to_datetime` to allow speedups for homogeneously formatted datetimes.
- Will intelligently limit display precision for datetime/timedelta formats.
- Enhanced Panel `apply()` method.

- Suggested tutorials in new Tutorials section.
- Our pandas ecosystem is growing, We now feature related projects in a new Pandas Ecosystem section.
- Much work has been taking place on improving the docs, and a new *Contributing* section has been added.
- Even though it may only be of interest to devs, we <3 our new CI status page: ScatterCI.

Warning: 0.13.1 fixes a bug that was caused by a combination of having numpy < 1.8, and doing chained assignment on a string-like array. Please review *the docs*, chained indexing can have unexpected results and should generally be avoided.

This would previously segfault:

```
In [1]: df = pd.DataFrame({"A": np.array(["foo", "bar", "bah", "foo", "bar"])})

In [2]: df["A"].iloc[0] = np.nan

In [3]: df
Out[3]:
     A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

The recommended way to do this type of assignment is:

```
In [4]: df = pd.DataFrame({"A": np.array(["foo", "bar", "bah", "foo", "bar"])})

In [5]: df.loc[0, "A"] = np.nan

In [6]: df
Out[6]:
     A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

Output formatting enhancements

- df.info() view now display dtype info per column (GH5682)
- df.info() now honors the option `max_info_rows`, to disable null counts for large frames (GH5974)

```
In [7]: max_info_rows = pd.get_option("max_info_rows")

In [8]: df = pd.DataFrame(
   ...:     {
   ...:         "A": np.random.randn(10),
   ...:         "B": np.random.randn(10),
   ...:         "C": pd.date_range("20130101", periods=10),
   ...:     }
   ...: )
```

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```
   ...:

In [9]: df.iloc[3:6, [0, 2]] = np.nan
```

```
# set to not display the null counts
In [10]: pd.set_option("max_info_rows", 0)

In [11]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
 #   Column  Dtype
---  ------  -----
 0   A       float64
 1   B       float64
 2   C       datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 368.0 bytes
```

```
# this is the default (same as in 0.13.0)
In [12]: pd.set_option("max_info_rows", max_info_rows)

In [13]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   A       7 non-null      float64
 1   B       10 non-null     float64
 2   C       7 non-null      datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 368.0 bytes
```

- Add `show_dimensions` display option for the new DataFrame repr to control whether the dimensions print.

```
In [14]: df = pd.DataFrame([[1, 2], [3, 4]])

In [15]: pd.set_option("show_dimensions", False)

In [16]: df
Out[16]:
   0  1
0  1  2
1  3  4

In [17]: pd.set_option("show_dimensions", True)

In [18]: df
Out[18]:
   0  1
0  1  2
1  3  4

[2 rows x 2 columns]
```

- The `ArrayFormatter` for `datetime` and `timedelta64` now intelligently limit precision based on the

values in the array (GH3401)

Previously output might look like:

```
  age                 today               diff
0 2001-01-01 00:00:00 2013-04-19 00:00:00 4491 days, 00:00:00
1 2004-06-01 00:00:00 2013-04-19 00:00:00 3244 days, 00:00:00
```

Now the output looks like:

```
In [19]: df = pd.DataFrame(
   ....:     [pd.Timestamp("20010101"), pd.Timestamp("20040601")], columns=["age"]
   ....: )
   ....:

In [20]: df["today"] = pd.Timestamp("20130419")

In [21]: df["diff"] = df["today"] - df["age"]

In [22]: df
Out[22]:
         age      today      diff
0 2001-01-01 2013-04-19 4491 days
1 2004-06-01 2013-04-19 3244 days

[2 rows x 3 columns]
```

API changes

- Add `-NaN` and `-nan` to the default set of NA values (GH5952). See *NA Values*.
- Added `Series.str.get_dummies` vectorized string method (GH6021), to extract dummy/indicator variables for separated string columns:

```
In [23]: s = pd.Series(["a", "a|b", np.nan, "a|c"])

In [24]: s.str.get_dummies(sep="|")
Out[24]:
   a  b  c
0  1  0  0
1  1  1  0
2  0  0  0
3  1  0  1

[4 rows x 3 columns]
```

- Added the `NDFrame.equals()` method to compare if two NDFrames are equal have equal axes, dtypes, and values. Added the `array_equivalent` function to compare if two ndarrays are equal. NaNs in identical locations are treated as equal. (GH5283) See also *the docs* for a motivating example.

```
df = pd.DataFrame({"col": ["foo", 0, np.nan]})
df2 = pd.DataFrame({"col": [np.nan, 0, "foo"]}, index=[2, 1, 0])
df.equals(df2)
df.equals(df2.sort_index())
```

- `DataFrame.apply` will use the `reduce` argument to determine whether a `Series` or a `DataFrame` should be returned when the `DataFrame` is empty (GH6007).

Previously, calling `DataFrame.apply` an empty `DataFrame` would return either a `DataFrame` if there were no columns, or the function being applied would be called with an empty `Series` to guess whether a `Series` or `DataFrame` should be returned:

```
In [32]: def applied_func(col):
  ....:     print("Apply function being called with: ", col)
  ....:     return col.sum()
  ....:

In [33]: empty = DataFrame(columns=['a', 'b'])

In [34]: empty.apply(applied_func)
Apply function being called with:  Series([], Length: 0, dtype: float64)
Out[34]:
a   NaN
b   NaN
Length: 2, dtype: float64
```

Now, when `apply` is called on an empty `DataFrame`: if the `reduce` argument is `True` a `Series` will returned, if it is `False` a `DataFrame` will be returned, and if it is `None` (the default) the function being applied will be called with an empty series to try and guess the return type.

```
In [35]: empty.apply(applied_func, reduce=True)
Out[35]:
a   NaN
b   NaN
Length: 2, dtype: float64

In [36]: empty.apply(applied_func, reduce=False)
Out[36]:
Empty DataFrame
Columns: [a, b]
Index: []

[0 rows x 2 columns]
```

Prior version deprecations/changes

There are no announced changes in 0.13 or prior that are taking effect as of 0.13.1

Deprecations

There are no deprecations of prior behavior in 0.13.1

Enhancements

- `pd.read_csv` and `pd.to_datetime` learned a new `infer_datetime_format` keyword which greatly improves parsing perf in many cases. Thanks to @lexual for suggesting and @danbirken for rapidly implementing. (GH5490, GH6021)

  If `parse_dates` is enabled and this flag is set, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.

```
# Try to infer the format for the index column
df = pd.read_csv(
    "foo.csv", index_col=0, parse_dates=True, infer_datetime_format=True
)
```

- `date_format` and `datetime_format` keywords can now be specified when writing to `excel` files (GH4133)
- `MultiIndex.from_product` convenience function for creating a MultiIndex from the cartesian product of a set of iterables (GH6055):

```
In [25]: shades = ["light", "dark"]

In [26]: colors = ["red", "green", "blue"]

In [27]: pd.MultiIndex.from_product([shades, colors], names=["shade", "color"])
Out[27]:
MultiIndex([('light',   'red'),
            ('light', 'green'),
            ('light',  'blue'),
            ( 'dark',   'red'),
            ( 'dark', 'green'),
            ( 'dark',  'blue')],
           names=['shade', 'color'])
```

- Panel `apply()` will work on non-ufuncs. See *the docs*.

```
In [28]: import pandas._testing as tm

In [29]: panel = tm.makePanel(5)

In [30]: panel
Out[30]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [31]: panel['ItemA']
Out[31]:
                   A         B         C         D
2000-01-03 -0.673690  0.577046 -1.344312 -1.469388
2000-01-04  0.113648 -1.715002  0.844885  0.357021
2000-01-05 -1.478427 -1.039268  1.075770 -0.674600
2000-01-06  0.524988 -0.370647 -0.109050 -1.776904
2000-01-07  0.404705 -1.157892  1.643563 -0.968914

[5 rows x 4 columns]
```

Specifying an `apply` that operates on a Series (to return a single element)

```
In [32]: panel.apply(lambda x: x.dtype, axis='items')
Out[32]:
                A        B        C        D
2000-01-03  float64  float64  float64  float64
2000-01-04  float64  float64  float64  float64
```

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```
2000-01-05  float64  float64  float64  float64
2000-01-06  float64  float64  float64  float64
2000-01-07  float64  float64  float64  float64

[5 rows x 4 columns]
```

A similar reduction type operation

```
In [33]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[33]:
      ItemA     ItemB     ItemC
A -1.108775 -1.090118 -2.984435
B -3.705764  0.409204  1.866240
C  2.110856  2.960500 -0.974967
D -4.532785  0.303202 -3.685193

[4 rows x 3 columns]
```

This is equivalent to

```
In [34]: panel.sum('major_axis')
Out[34]:
      ItemA     ItemB     ItemC
A -1.108775 -1.090118 -2.984435
B -3.705764  0.409204  1.866240
C  2.110856  2.960500 -0.974967
D -4.532785  0.303202 -3.685193

[4 rows x 3 columns]
```

A transformation operation that returns a Panel, but is computing the z-score across the major_axis

```
In [35]: result = panel.apply(lambda x: (x - x.mean()) / x.std(),
  ....:                       axis='major_axis')
  ....:

In [36]: result
Out[36]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [37]: result['ItemA']                          # noqa E999
Out[37]:
                   A         B         C         D
2000-01-03 -0.535778  1.500802 -1.506416 -0.681456
2000-01-04  0.397628 -1.108752  0.360481  1.529895
2000-01-05 -1.489811 -0.339412  0.557374  0.280845
2000-01-06  0.885279  0.421830 -0.453013 -1.053785
2000-01-07  0.742682 -0.474468  1.041575 -0.075499

[5 rows x 4 columns]
```

- Panel `apply()` operating on cross-sectional slabs. (GH1148)

```
In [38]: def f(x):
   ....:     return ((x.T - x.mean(1)) / x.std(1)).T
   ....:

In [39]: result = panel.apply(f, axis=['items', 'major_axis'])

In [40]: result
Out[40]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [41]: result.loc[:, :, 'ItemA']
Out[41]:
                   A         B         C         D
2000-01-03  0.012922 -0.030874 -0.629546 -0.757034
2000-01-04  0.392053 -1.071665  0.163228  0.548188
2000-01-05 -1.093650 -0.640898  0.385734 -1.154310
2000-01-06  1.005446 -1.154593 -0.595615 -0.809185
2000-01-07  0.783051 -0.198053  0.919339 -1.052721

[5 rows x 4 columns]
```

This is equivalent to the following

```
In [42]: result = pd.Panel({ax: f(panel.loc[:, :, ax]) for ax in panel.minor_axis}
 ↪)

In [43]: result
Out[43]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [44]: result.loc[:, :, 'ItemA']
Out[44]:
                   A         B         C         D
2000-01-03  0.012922 -0.030874 -0.629546 -0.757034
2000-01-04  0.392053 -1.071665  0.163228  0.548188
2000-01-05 -1.093650 -0.640898  0.385734 -1.154310
2000-01-06  1.005446 -1.154593 -0.595615 -0.809185
2000-01-07  0.783051 -0.198053  0.919339 -1.052721

[5 rows x 4 columns]
```

Performance

Performance improvements for 0.13.1

- Series datetime/timedelta binary operations (GH5801)
- DataFrame `count/dropna` for `axis=1`
- Series.str.contains now has a `regex=False` keyword which can be faster for plain (non-regex) string patterns. (GH5879)
- Series.str.extract (GH5944)
- `dtypes/ftypes` methods (GH5968)
- indexing with object dtypes (GH5968)
- `DataFrame.apply` (GH6013)
- Regression in JSON IO (GH5765)
- Index construction from Series (GH6150)

Experimental

There are no experimental changes in 0.13.1

Bug fixes

- Bug in `io.wb.get_countries` not including all countries (GH6008)
- Bug in Series replace with timestamp dict (GH5797)
- read_csv/read_table now respects the `prefix` kwarg (GH5732).
- Bug in selection with missing values via `.ix` from a duplicate indexed DataFrame failing (GH5835)
- Fix issue of boolean comparison on empty DataFrames (GH5808)
- Bug in isnull handling `NaT` in an object array (GH5443)
- Bug in `to_datetime` when passed a `np.nan` or integer datelike and a format string (GH5863)
- Bug in groupby dtype conversion with datetimelike (GH5869)
- Regression in handling of empty Series as indexers to Series (GH5877)
- Bug in internal caching, related to (GH5727)
- Testing bug in reading JSON/msgpack from a non-filepath on windows under py3 (GH5874)
- Bug when assigning to .ix[tuple(...)] (GH5896)
- Bug in fully reindexing a Panel (GH5905)
- Bug in idxmin/max with object dtypes (GH5914)
- Bug in `BusinessDay` when adding n days to a date not on offset when n>5 and n%5==0 (GH5890)
- Bug in assigning to chained series with a series via ix (GH5928)
- Bug in creating an empty DataFrame, copying, then assigning (GH5932)
- Bug in DataFrame.tail with empty frame (GH5846)
- Bug in propagating metadata on `resample` (GH5862)

- Fixed string-representation of `NaT` to be "NaT" (GH5708)
- Fixed string-representation for Timestamp to show nanoseconds if present (GH5912)
- `pd.match` not returning passed sentinel
- `Panel.to_frame()` no longer fails when `major_axis` is a `MultiIndex` (GH5402).
- Bug in `pd.read_msgpack` with inferring a `DateTimeIndex` frequency incorrectly (GH5947)
- Fixed `to_datetime` for array with both Tz-aware datetimes and `NaT`'s (GH5961)
- Bug in rolling skew/kurtosis when passed a Series with bad data (GH5749)
- Bug in scipy `interpolate` methods with a datetime index (GH5975)
- Bug in NaT comparison if a mixed datetime/np.datetime64 with NaT were passed (GH5968)
- Fixed bug with `pd.concat` losing dtype information if all inputs are empty (GH5742)
- Recent changes in IPython cause warnings to be emitted when using previous versions of pandas in QTConsole, now fixed. If you're using an older version and need to suppress the warnings, see (GH5922).
- Bug in merging `timedelta` dtypes (GH5695)
- Bug in plotting.scatter_matrix function. Wrong alignment among diagonal and off-diagonal plots, see (GH5497).
- Regression in Series with a MultiIndex via ix (GH6018)
- Bug in Series.xs with a MultiIndex (GH6018)
- Bug in Series construction of mixed type with datelike and an integer (which should result in object type and not automatic conversion) (GH6028)
- Possible segfault when chained indexing with an object array under NumPy 1.7.1 (GH6026, GH6056)
- Bug in setting using fancy indexing a single element with a non-scalar (e.g. a list), (GH6043)
- `to_sql` did not respect `if_exists` (GH4110 GH4304)
- Regression in `.get(None)` indexing from 0.12 (GH5652)
- Subtle `iloc` indexing bug, surfaced in (GH6059)
- Bug with insert of strings into DatetimeIndex (GH5818)
- Fixed unicode bug in to_html/HTML repr (GH6098)
- Fixed missing arg validation in get_options_data (GH6105)
- Bug in assignment with duplicate columns in a frame where the locations are a slice (e.g. next to each other) (GH6120)
- Bug in propagating _ref_locs during construction of a DataFrame with dups index/columns (GH6121)
- Bug in `DataFrame.apply` when using mixed datelike reductions (GH6125)
- Bug in `DataFrame.append` when appending a row with different columns (GH6129)
- Bug in DataFrame construction with recarray and non-ns datetime dtype (GH6140)
- Bug in `.loc` setitem indexing with a dataframe on rhs, multiple item setting, and a datetimelike (GH6152)
- Fixed a bug in `query`/`eval` during lexicographic string comparisons (GH6155).
- Fixed a bug in `query` where the index of a single-element `Series` was being thrown away (GH6148).
- Bug in `HDFStore` on appending a dataframe with MultiIndexed columns to an existing table (GH6167)

- Consistency with dtypes in setting an empty DataFrame (GH6171)
- Bug in selecting on a MultiIndex `HDFStore` even in the presence of under specified column spec (GH6169)
- Bug in `nanops.var` with `ddof=1` and 1 elements would sometimes return `inf` rather than `nan` on some platforms (GH6136)
- Bug in Series and DataFrame bar plots ignoring the `use_index` keyword (GH6209)
- Bug in groupby with mixed str/int under python3 fixed; `argsort` was failing (GH6212)

Contributors

A total of 52 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Alex Rothberg
- Alok Singhal +
- Andrew Burrows +
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- Bjorn Arneson +
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- Clark Fitzgerald +
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- danielballan
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- mwaskom +
- unutbu
- y-p

5.16.2 Version 0.13.0 (January 3, 2014)

This is a major release from 0.12.0 and includes a number of API changes, several new features and enhancements along with a large number of bug fixes.

Highlights include:

- support for a new index type `Float64Index`, and other Indexing enhancements
- `HDFStore` has a new string based syntax for query specification
- support for new methods of interpolation
- updated `timedelta` operations
- a new string manipulation method `extract`
- Nanosecond support for Offsets

- `isin` for DataFrames

Several experimental features are added, including:

- new `eval/query` methods for expression evaluation
- support for `msgpack` serialization
- an i/o interface to Google's `BigQuery`

Their are several new or updated docs sections including:

- *Comparison with SQL*, which should be useful for those familiar with SQL but still learning pandas.
- *Comparison with R*, idiom translations from R to pandas.
- *Enhancing Performance*, ways to enhance pandas performance with `eval/query`.

Warning: In 0.13.0 `Series` has internally been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, similar to the rest of the pandas containers. This should be a transparent change with only very limited API implications. See *Internal Refactoring*

API changes

- `read_excel` now supports an integer in its `sheetname` argument giving the index of the sheet to read in (GH4301).
- Text parser now treats anything that reads like inf ("inf", "Inf", "-Inf", "iNf", etc.) as infinity. (GH4220, GH4219), affecting `read_table`, `read_csv`, etc.
- `pandas` now is Python 2/3 compatible without the need for 2to3 thanks to @jtratner. As a result, pandas now uses iterators more extensively. This also led to the introduction of substantive parts of the Benjamin Peterson's `six` library into compat. (GH4384, GH4375, GH4372)
- `pandas.util.compat` and `pandas.util.py3compat` have been merged into `pandas.compat`. `pandas.compat` now includes many functions allowing 2/3 compatibility. It contains both list and iterator versions of range, filter, map and zip, plus other necessary elements for Python 3 compatibility. `lmap`, `lzip`, `lrange` and `lfilter` all produce lists instead of iterators, for compatibility with `numpy`, subscripting and `pandas` constructors.(GH4384, GH4375, GH4372)
- `Series.get` with negative indexers now returns the same as `[]` (GH4390)
- Changes to how `Index` and `MultiIndex` handle metadata (`levels`, `labels`, and `names`) (GH4039):

```
# previously, you would have set levels or labels directly
>>> pd.index.levels = [[1, 2, 3, 4], [1, 2, 4, 4]]

# now, you use the set_levels or set_labels methods
>>> index = pd.index.set_levels([[1, 2, 3, 4], [1, 2, 4, 4]])

# similarly, for names, you can rename the object
# but setting names is not deprecated
>>> index = pd.index.set_names(["bob", "cranberry"])

# and all methods take an inplace kwarg - but return None
>>> pd.index.set_names(["bob", "cranberry"], inplace=True)
```

- **All** division with `NDFrame` objects is now *truedivision*, regardless of the future import. This means that operating on pandas objects will by default use *floating point* division, and return a floating point dtype. You can use `//` and `floordiv` to do integer division.

Integer division

```
In [3]: arr = np.array([1, 2, 3, 4])

In [4]: arr2 = np.array([5, 3, 2, 1])

In [5]: arr / arr2
Out[5]: array([0, 0, 1, 4])

In [6]: pd.Series(arr) // pd.Series(arr2)
Out[6]:
0    0
1    0
2    1
3    4
dtype: int64
```

True Division

```
In [7]: pd.Series(arr) / pd.Series(arr2)  # no future import required
Out[7]:
0    0.200000
1    0.666667
2    1.500000
3    4.000000
dtype: float64
```

- Infer and downcast dtype if `downcast='infer'` is passed to `fillna/ffill/bfill` (GH4604)
- `__nonzero__` for all NDFrame objects, will now raise a `ValueError`, this reverts back to (GH1073, GH4633) behavior. See *gotchas* for a more detailed discussion.

  This prevents doing boolean comparison on *entire* pandas objects, which is inherently ambiguous. These all will raise a `ValueError`.

```
>>> df = pd.DataFrame({'A': np.random.randn(10),
...                    'B': np.random.randn(10),
...                    'C': pd.date_range('20130101', periods=10)
...                    })
...
>>> if df:
...     pass
...
Traceback (most recent call last):
    ...
ValueError: The truth value of a DataFrame is ambiguous.  Use a.empty,
a.bool(), a.item(), a.any() or a.all().

>>> df1 = df
>>> df2 = df
>>> df1 and df2
Traceback (most recent call last):
    ...
ValueError: The truth value of a DataFrame is ambiguous.  Use a.empty,
a.bool(), a.item(), a.any() or a.all().

>>> d = [1, 2, 3]
>>> s1 = pd.Series(d)
>>> s2 = pd.Series(d)
```

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```
>>> s1 and s2
Traceback (most recent call last):
    ...
ValueError: The truth value of a DataFrame is ambiguous.  Use a.empty,
a.bool(), a.item(), a.any() or a.all().
```

Added the `.bool()` method to `NDFrame` objects to facilitate evaluating of single-element boolean Series:

```
In [1]: pd.Series([True]).bool()
Out[1]: True

In [2]: pd.Series([False]).bool()
Out[2]: False

In [3]: pd.DataFrame([[True]]).bool()
Out[3]: True

In [4]: pd.DataFrame([[False]]).bool()
Out[4]: False
```

- All non-Index NDFrames (`Series`, `DataFrame`, `Panel`, `Panel4D`, `SparsePanel`, etc.), now support the entire set of arithmetic operators and arithmetic flex methods (add, sub, mul, etc.). `SparsePanel` does not support `pow` or `mod` with non-scalars. (GH3765)
- `Series` and `DataFrame` now have a `mode()` method to calculate the statistical mode(s) by axis/Series. (GH5367)
- Chained assignment will now by default warn if the user is assigning to a copy. This can be changed with the option `mode.chained_assignment`, allowed options are `raise/warn/None`. See *the docs*.

```
In [5]: dfc = pd.DataFrame({'A': ['aaa', 'bbb', 'ccc'], 'B': [1, 2, 3]})

In [6]: pd.set_option('chained_assignment', 'warn')
```

The following warning / exception will show if this is attempted.

```
In [7]: dfc.loc[0]['A'] = 1111
```

```
Traceback (most recent call last)
   ...
SettingWithCopyWarning:
   A value is trying to be set on a copy of a slice from a DataFrame.
   Try using .loc[row_index,col_indexer] = value instead
```

Here is the correct method of assignment.

```
In [8]: dfc.loc[0, 'A'] = 11

In [9]: dfc
Out[9]:
     A  B
0   11  1
1  bbb  2
2  ccc  3
```

- **`Panel.reindex` has the following call signature `Panel.reindex(items=None, major_axis=None, minor_a`**
  to conform with other `NDFrame` objects. See *Internal Refactoring* for more information.

- **`Series.argmin` and `Series.argmax` are now aliased to `Series.idxmin` and `Series.idxmax`. These return the *i*** min or max element respectively. Prior to 0.13.0 these would return the position of the min / max element. (GH6214)

Prior version deprecations/changes

These were announced changes in 0.12 or prior that are taking effect as of 0.13.0

- Remove deprecated `Factor` (GH3650)
- Remove deprecated `set_printoptions/reset_printoptions` (GH3046)
- Remove deprecated `_verbose_info` (GH3215)
- Remove deprecated `read_clipboard/to_clipboard/ExcelFile/ExcelWriter` from `pandas.io.parsers` (GH3717) These are available as functions in the main pandas namespace (e.g. `pd.read_clipboard`)
- default for `tupleize_cols` is now `False` for both `to_csv` and `read_csv`. Fair warning in 0.12 (GH3604)
- default for `display.max_seq_len` is now 100 rather than `None`. This activates truncated display ("...") of long sequences in various places. (GH3391)

Deprecations

Deprecated in 0.13.0

- deprecated `iterkv`, which will be removed in a future release (this was an alias of iteritems used to bypass `2to3`'s changes). (GH4384, GH4375, GH4372)
- deprecated the string method `match`, whose role is now performed more idiomatically by `extract`. In a future release, the default behavior of `match` will change to become analogous to `contains`, which returns a boolean indexer. (Their distinction is strictness: `match` relies on `re.match` while `contains` relies on `re.search`.) In this release, the deprecated behavior is the default, but the new behavior is available through the keyword argument `as_indexer=True`.

Indexing API changes

Prior to 0.13, it was impossible to use a label indexer (`.loc/.ix`) to set a value that was not contained in the index of a particular axis. (GH2578). See *the docs*

In the `Series` case this is effectively an appending operation

```
In [10]: s = pd.Series([1, 2, 3])

In [11]: s
Out[11]:
0    1
1    2
2    3
dtype: int64

In [12]: s[5] = 5.

In [13]: s
Out[13]:
```

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```
0    1.0
1    2.0
2    3.0
5    5.0
dtype: float64
```

```
In [14]: dfi = pd.DataFrame(np.arange(6).reshape(3, 2),
   ....:                    columns=['A', 'B'])
   ....:

In [15]: dfi
Out[15]:
   A  B
0  0  1
1  2  3
2  4  5
```

This would previously `KeyError`

```
In [16]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']

In [17]: dfi
Out[17]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
```

This is like an `append` operation.

```
In [18]: dfi.loc[3] = 5

In [19]: dfi
Out[19]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

A Panel setting operation on an arbitrary axis aligns the input to the Panel

```
In [20]: p = pd.Panel(np.arange(16).reshape(2, 4, 2),
   ....:              items=['Item1', 'Item2'],
   ....:              major_axis=pd.date_range('2001/1/12', periods=4),
   ....:              minor_axis=['A', 'B'], dtype='float64')
   ....:

In [21]: p
Out[21]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to B
```

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```
In [22]: p.loc[:, :, 'C'] = pd.Series([30, 32], index=p.items)

In [23]: p
Out[23]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to C

In [24]: p.loc[:, :, 'C']
Out[24]:
             Item1  Item2
2001-01-12   30.0   32.0
2001-01-13   30.0   32.0
2001-01-14   30.0   32.0
2001-01-15   30.0   32.0
```

Float64Index API change

- Added a new index type, `Float64Index`. This will be automatically created when passing floating values in index creation. This enables a pure label-based slicing paradigm that makes `[],ix,loc` for scalar indexing and slicing work exactly the same. See *the docs*, (GH263)

  Construction is by default for floating type values.

```
In [20]: index = pd.Index([1.5, 2, 3, 4.5, 5])

In [21]: index
Out[21]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')

In [22]: s = pd.Series(range(5), index=index)

In [23]: s
Out[23]:
1.5    0
2.0    1
3.0    2
4.5    3
5.0    4
dtype: int64
```

  Scalar selection for `[],.ix,.loc` will always be label based. An integer will match an equal float index (e.g. `3` is equivalent to `3.0`)

```
In [24]: s[3]
Out[24]: 2

In [25]: s.loc[3]
Out[25]: 2
```

  The only positional indexing is via `iloc`

```
In [26]: s.iloc[3]
Out[26]: 3
```

A scalar index that is not found will raise `KeyError`

Slicing is ALWAYS on the values of the index, for `[]`, `ix`, `loc` and ALWAYS positional with `iloc`

```
In [27]: s[2:4]
Out[27]:
2.0    1
3.0    2
dtype: int64

In [28]: s.loc[2:4]
Out[28]:
2.0    1
3.0    2
dtype: int64

In [29]: s.iloc[2:4]
Out[29]:
3.0    2
4.5    3
dtype: int64
```

In float indexes, slicing using floats are allowed

```
In [30]: s[2.1:4.6]
Out[30]:
3.0    2
4.5    3
dtype: int64

In [31]: s.loc[2.1:4.6]
Out[31]:
3.0    2
4.5    3
dtype: int64
```

- Indexing on other index types are preserved (and positional fallback for `[]`, `ix`), with the exception, that floating point slicing on indexes on non `Float64Index` will now raise a `TypeError`.

```
In [1]: pd.Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type␣
↪(Int64Index)

In [1]: pd.Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type␣
↪(Int64Index)
```

Using a scalar float indexer will be deprecated in a future version, but is allowed for now.

```
In [3]: pd.Series(range(5))[3.0]
Out[3]: 3
```

HDFStore API changes

- Query Format Changes. A much more string-like query format is now supported. See *the docs*.

```
In [32]: path = 'test.h5'

In [33]: dfq = pd.DataFrame(np.random.randn(10, 4),
   ....:                    columns=list('ABCD'),
   ....:                    index=pd.date_range('20130101', periods=10))
   ....:

In [34]: dfq.to_hdf(path, 'dfq', format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```
In [35]: pd.read_hdf(path, 'dfq',
   ....:             where="index>Timestamp('20130104') & columns=['A', 'B']")
   ....:
Out[35]:
                   A         B
2013-01-05 -0.424972  0.567020
2013-01-06 -0.673690  0.113648
2013-01-07  0.404705  0.577046
2013-01-08 -0.370647 -1.157892
2013-01-09  1.075770 -0.109050
2013-01-10  0.357021 -0.674600
```

Use an inline column reference

```
In [36]: pd.read_hdf(path, 'dfq',
   ....:             where="A>0 or C>0")
   ....:
Out[36]:
                   A         B         C         D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
2013-01-07  0.404705  0.577046 -1.715002 -1.039268
2013-01-09  1.075770 -0.109050  1.643563 -1.469388
2013-01-10  0.357021 -0.674600 -1.776904 -0.968914
```

- the `format` keyword now replaces the `table` keyword; allowed values are `fixed(f)` or `table(t)` the same defaults as prior < 0.13.0 remain, e.g. `put` implies `fixed` format and `append` implies `table` format. This default format can be set as an option by setting `io.hdf.default_format`.

```
In [37]: path = 'test.h5'

In [38]: df = pd.DataFrame(np.random.randn(10, 2))

In [39]: df.to_hdf(path, 'df_table', format='table')

In [40]: df.to_hdf(path, 'df_table2', append=True)

In [41]: df.to_hdf(path, 'df_fixed')

In [42]: with pd.HDFStore(path) as store:
   ....:     print(store)
```

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```
   ....:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
```

- Significant table writing performance improvements
- handle a passed `Series` in table format (GH4330)
- can now serialize a `timedelta64[ns]` dtype in a table (GH3577), See *the docs*.
- added an `is_open` property to indicate if the underlying file handle is_open; a closed store will now report 'CLOSED' when viewing the store (rather than raising an error) (GH4409)
- a close of a `HDFStore` now will close that instance of the `HDFStore` but will only close the actual file if the ref count (by `PyTables`) w.r.t. all of the open handles are 0. Essentially you have a local instance of `HDFStore` referenced by a variable. Once you close it, it will report closed. Other references (to the same file) will continue to operate until they themselves are closed. Performing an action on a closed file will raise `ClosedFileError`

```
In [43]: path = 'test.h5'

In [44]: df = pd.DataFrame(np.random.randn(10, 2))

In [45]: store1 = pd.HDFStore(path)

In [46]: store2 = pd.HDFStore(path)

In [47]: store1.append('df', df)

In [48]: store2.append('df2', df)

In [49]: store1
Out[49]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5

In [50]: store2
Out[50]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5

In [51]: store1.close()

In [52]: store2
Out[52]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5

In [53]: store2.close()

In [54]: store2
Out[54]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
```

- removed the `_quiet` attribute, replace by a `DuplicateWarning` if retrieving duplicate rows from a table (GH4367)

- removed the `warn` argument from `open`. Instead a `PossibleDataLossError` exception will be raised if you try to use `mode='w'` with an OPEN file handle (GH4367)
- allow a passed locations array or mask as a `where` condition (GH4467). See *the docs* for an example.
- add the keyword `dropna=True` to `append` to change whether ALL nan rows are not written to the store (default is `True`, ALL nan rows are NOT written), also settable via the option `io.hdf.dropna_table` (GH4625)
- pass through store creation arguments; can be used to support in-memory stores

DataFrame repr changes

The HTML and plain text representations of *`DataFrame`* now show a truncated view of the table once it exceeds a certain size, rather than switching to the short info view (GH4886, GH5550). This makes the representation more consistent as small DataFrames get larger.

2010-03-29	13.70	13.88	13.39	13.57	158225000	12.98
2010-03-30	13.55	13.64	13.18	13.28	142055200	12.70
	...	...	...	...	...	...

771 rows × 6 columns

To get the info view, call *`DataFrame.info()`*. If you prefer the info view as the repr for large DataFrames, you can set this by running `set_option('display.large_repr', 'info')`.

Enhancements

- `df.to_clipboard()` learned a new `excel` keyword that let's you paste df data directly into excel (enabled by default). (GH5070).
- `read_html` now raises a `URLError` instead of catching and raising a `ValueError` (GH4303, GH4305)
- Added a test for `read_clipboard()` and `to_clipboard()` (GH4282)
- Clipboard functionality now works with PySide (GH4282)
- Added a more informative error message when plot arguments contain overlapping color and style arguments (GH4402)
- `to_dict` now takes `records` as a possible out type. Returns an array of column-keyed dictionaries. (GH4936)
- `NaN` handing in get_dummies (GH4446) with `dummy_na`

```
# previously, nan was erroneously counted as 2 here
# now it is not counted at all
In [55]: pd.get_dummies([1, 2, np.nan])
Out[55]:
   1.0  2.0
0    1    0
1    0    1
2    0    0

# unless requested
```

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```
In [56]: pd.get_dummies([1, 2, np.nan], dummy_na=True)
Out[56]:
   1.0  2.0  NaN
0    1    0    0
1    0    1    0
2    0    0    1
```

- `timedelta64[ns]` operations. See *the docs*.

> **Warning:** Most of these operations require `numpy >= 1.7`

Using the new top-level `to_timedelta`, you can convert a scalar or array from the standard timedelta format (produced by `to_csv`) into a timedelta type (`np.timedelta64` in `nanoseconds`).

```
In [57]: pd.to_timedelta('1 days 06:05:01.00003')
Out[57]: Timedelta('1 days 06:05:01.000030')

In [58]: pd.to_timedelta('15.5us')
Out[58]: Timedelta('0 days 00:00:00.000015500')

In [59]: pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
Out[59]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015500',␣
↪NaT], dtype='timedelta64[ns]', freq=None)

In [60]: pd.to_timedelta(np.arange(5), unit='s')
Out[60]:
TimedeltaIndex(['0 days 00:00:00', '0 days 00:00:01', '0 days 00:00:02',
                '0 days 00:00:03', '0 days 00:00:04'],
               dtype='timedelta64[ns]', freq=None)

In [61]: pd.to_timedelta(np.arange(5), unit='d')
Out[61]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype=
↪'timedelta64[ns]', freq=None)
```

A Series of dtype `timedelta64[ns]` can now be divided by another `timedelta64[ns]` object, or astyped to yield a `float64` dtyped Series. This is frequency conversion. See *the docs* for the docs.

```
In [62]: import datetime

In [63]: td = pd.Series(pd.date_range('20130101', periods=4)) - pd.Series(
   ....:     pd.date_range('20121201', periods=4))
   ....:

In [64]: td[2] += np.timedelta64(datetime.timedelta(minutes=5, seconds=3))

In [65]: td[3] = np.nan

In [66]: td
Out[66]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3                NaT
dtype: timedelta64[ns]
```

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```
# to days
In [67]: td / np.timedelta64(1, 'D')
Out[67]:
0    31.000000
1    31.000000
2    31.003507
3          NaN
dtype: float64

In [68]: td.astype('timedelta64[D]')
Out[68]:
0    31.0
1    31.0
2    31.0
3     NaN
dtype: float64

# to seconds
In [69]: td / np.timedelta64(1, 's')
Out[69]:
0    2678400.0
1    2678400.0
2    2678703.0
3          NaN
dtype: float64

In [70]: td.astype('timedelta64[s]')
Out[70]:
0    2678400.0
1    2678400.0
2    2678703.0
3          NaN
dtype: float64
```

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series

```
In [71]: td * -1
Out[71]:
0   -31 days +00:00:00
1   -31 days +00:00:00
2   -32 days +23:54:57
3                  NaT
dtype: timedelta64[ns]

In [72]: td * pd.Series([1, 2, 3, 4])
Out[72]:
0   31 days 00:00:00
1   62 days 00:00:00
2   93 days 00:15:09
3               NaT
dtype: timedelta64[ns]
```

Absolute `DateOffset` objects can act equivalently to `timedeltas`

```
In [73]: from pandas import offsets

In [74]: td + offsets.Minute(5) + offsets.Milli(5)
```

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```
Out[74]:
0   31 days 00:05:00.005000
1   31 days 00:05:00.005000
2   31 days 00:10:03.005000
3                       NaT
dtype: timedelta64[ns]
```

Fillna is now supported for timedeltas

```
In [75]: td.fillna(pd.Timedelta(0))
Out[75]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3    0 days 00:00:00
dtype: timedelta64[ns]

In [76]: td.fillna(datetime.timedelta(days=1, seconds=5))
Out[76]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3    1 days 00:00:05
dtype: timedelta64[ns]
```

You can do numeric reduction operations on timedeltas.

```
In [77]: td.mean()
Out[77]: Timedelta('31 days 00:01:41')

In [78]: td.quantile(.1)
Out[78]: Timedelta('31 days 00:00:00')
```

- `plot(kind='kde')` now accepts the optional parameters `bw_method` and `ind`, passed to scipy.stats.gaussian_kde() (for scipy >= 0.11.0) to set the bandwidth, and to gkde.evaluate() to specify the indices at which it is evaluated, respectively. See scipy docs. (GH4298)
- DataFrame constructor now accepts a numpy masked record array (GH3478)
- The new vectorized string method `extract` return regular expression matches more conveniently.

```
In [79]: pd.Series(['a1', 'b2', 'c3']).str.extract('[ab](\\d)')
Out[79]:
     0
0    1
1    2
2  NaN
```

Elements that do not match return `NaN`. Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```
In [80]: pd.Series(['a1', 'b2', 'c3']).str.extract('([ab])(\\d)')
Out[80]:
     0    1
0    a    1
1    b    2
2  NaN  NaN
```

Elements that do not match return a row of NaN. Thus, a Series of messy strings can be *converted* into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating `get()` to access tuples or `re.match` objects.

Named groups like

```
In [81]: pd.Series(['a1', 'b2', 'c3']).str.extract(
   ....:     '(?P<letter>[ab])(?P<digit>\\d)')
   ....:
Out[81]:
  letter digit
0      a     1
1      b     2
2    NaN   NaN
```

and optional groups can also be used.

```
In [82]: pd.Series(['a1', 'b2', '3']).str.extract(
   ....:     '(?P<letter>[ab])?(?P<digit>\\d)')
   ....:
Out[82]:
  letter digit
0      a     1
1      b     2
2    NaN     3
```

- `read_stata` now accepts Stata 13 format (GH4291)
- `read_fwf` now infers the column specifications from the first 100 rows of the file if the data has correctly separated and properly aligned columns using the delimiter provided to the function (GH4488).
- support for nanosecond times as an offset

> **Warning:** These operations require `numpy >= 1.7`

Period conversions in the range of seconds and below were reworked and extended up to nanoseconds. Periods in the nanosecond range are now available.

```
In [83]: pd.date_range('2013-01-01', periods=5, freq='5N')
Out[83]:
DatetimeIndex([          '2013-01-01 00:00:00',
               '2013-01-01 00:00:00.000000005',
               '2013-01-01 00:00:00.000000010',
               '2013-01-01 00:00:00.000000015',
               '2013-01-01 00:00:00.000000020'],
              dtype='datetime64[ns]', freq='5N')
```

or with frequency as offset

```
In [84]: pd.date_range('2013-01-01', periods=5, freq=pd.offsets.Nano(5))
Out[84]:
DatetimeIndex([          '2013-01-01 00:00:00',
               '2013-01-01 00:00:00.000000005',
               '2013-01-01 00:00:00.000000010',
               '2013-01-01 00:00:00.000000015',
               '2013-01-01 00:00:00.000000020'],
              dtype='datetime64[ns]', freq='5N')
```

Timestamps can be modified in the nanosecond range

```
In [85]: t = pd.Timestamp('20130101 09:01:02')

In [86]: t + pd.tseries.offsets.Nano(123)
Out[86]: Timestamp('2013-01-01 09:01:02.000000123')
```

- A new method, `isin` for DataFrames, which plays nicely with boolean indexing. The argument to `isin`, what we're comparing the DataFrame to, can be a DataFrame, Series, dict, or array of values. See *the docs* for more.

  To get the rows where any of the conditions are met:

```
In [87]: dfi = pd.DataFrame({'A': [1, 2, 3, 4], 'B': ['a', 'b', 'f', 'n']})

In [88]: dfi
Out[88]:
   A  B
0  1  a
1  2  b
2  3  f
3  4  n

In [89]: other = pd.DataFrame({'A': [1, 3, 3, 7], 'B': ['e', 'f', 'f', 'e']})

In [90]: mask = dfi.isin(other)

In [91]: mask
Out[91]:
       A      B
0   True  False
1  False  False
2   True   True
3  False  False

In [92]: dfi[mask.any(1)]
Out[92]:
   A  B
0  1  a
2  3  f
```

- `Series` now supports a `to_frame` method to convert it to a single-column DataFrame (GH5164)
- All R datasets listed here http://stat.ethz.ch/R-manual/R-devel/library/datasets/html/00Index.html can now be loaded into pandas objects

```
# note that pandas.rpy was deprecated in v0.16.0
import pandas.rpy.common as com
com.load_data('Titanic')
```

- `tz_localize` can infer a fall daylight savings transition based on the structure of the unlocalized data (GH4230), see *the docs*
- `DatetimeIndex` is now in the API documentation, see *the docs*
- `json_normalize()` is a new method to allow you to create a flat table from semi-structured JSON data. See *the docs* (GH1067)
- Added PySide support for the qtpandas DataFrameModel and DataFrameWidget.
- Python csv parser now supports usecols (GH4335)

- Frequencies gained several new offsets:
  - `LastWeekOfMonth` (GH4637)
  - `FY5253`, and `FY5253Quarter` (GH4511)
- DataFrame has a new `interpolate` method, similar to Series (GH4434, GH1892)

```
In [93]: df = pd.DataFrame({'A': [1, 2.1, np.nan, 4.7, 5.6, 6.8],
   ....:                    'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})
   ....:

In [94]: df.interpolate()
Out[94]:
     A      B
0  1.0   0.25
1  2.1   1.50
2  3.4   2.75
3  4.7   4.00
4  5.6  12.20
5  6.8  14.40
```

Additionally, the `method` argument to `interpolate` has been expanded to include `'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'piecewise_polynomial', 'pchip', 'polynomial', 'spline'` The new methods require scipy. Consult the Scipy reference guide and documentation for more information about when the various methods are appropriate. See *the docs*.

Interpolate now also accepts a `limit` keyword argument. This works similar to `fillna`'s limit:

```
In [95]: ser = pd.Series([1, 3, np.nan, np.nan, np.nan, 11])

In [96]: ser.interpolate(limit=2)
Out[96]:
0     1.0
1     3.0
2     5.0
3     7.0
4     NaN
5    11.0
dtype: float64
```

- Added `wide_to_long` panel data convenience function. See *the docs*.

```
In [97]: np.random.seed(123)

In [98]: df = pd.DataFrame({"A1970" : {0 : "a", 1 : "b", 2 : "c"},
   ....:                    "A1980" : {0 : "d", 1 : "e", 2 : "f"},
   ....:                    "B1970" : {0 : 2.5, 1 : 1.2, 2 : .7},
   ....:                    "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1},
   ....:                    "X"     : dict(zip(range(3), np.random.randn(3)))
   ....:                   })
   ....:

In [99]: df["id"] = df.index

In [100]: df
Out[100]:
  A1970 A1980  B1970  B1980         X  id
```

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```
0     a     d    2.5    3.2 -1.085631   0
1     b     e    1.2    1.3  0.997345   1
2     c     f    0.7    0.1  0.282978   2

In [101]: pd.wide_to_long(df, ["A", "B"], i="id", j="year")
Out[101]:
                X  A    B
id year
0  1970 -1.085631  a  2.5
1  1970  0.997345  b  1.2
2  1970  0.282978  c  0.7
0  1980 -1.085631  d  3.2
1  1980  0.997345  e  1.3
2  1980  0.282978  f  0.1
```

- `to_csv` now takes a `date_format` keyword argument that specifies how output datetime objects should be formatted. Datetimes encountered in the index, columns, and values will all have this formatting applied. (GH4313)
- `DataFrame.plot` will scatter plot x versus y by passing `kind='scatter'` (GH2215)
- Added support for Google Analytics v3 API segment IDs that also supports v2 IDs. (GH5271)

Experimental

- The new *`eval()`* function implements expression evaluation using `numexpr` behind the scenes. This results in large speedups for complicated expressions involving large DataFrames/Series. For example,

```
In [102]: nrows, ncols = 20000, 100

In [103]: df1, df2, df3, df4 = [pd.DataFrame(np.random.randn(nrows, ncols))
   .....:                       for _ in range(4)]
   .....:
```

```
# eval with NumExpr backend
In [104]: %timeit pd.eval('df1 + df2 + df3 + df4')
5.31 ms +- 45.9 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
# pure Python evaluation
In [105]: %timeit df1 + df2 + df3 + df4
6.03 ms +- 344 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

  For more details, see the *the docs*

- Similar to `pandas.eval`, *`DataFrame`* has a new `DataFrame.eval` method that evaluates an expression in the context of the `DataFrame`. For example,

```
In [106]: df = pd.DataFrame(np.random.randn(10, 2), columns=['a', 'b'])

In [107]: df.eval('a + b')
Out[107]:
0   -0.685204
1    1.589745
2    0.325441
3   -1.784153
```

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```
4   -0.432893
5    0.171850
6    1.895919
7    3.065587
8   -0.092759
9    1.391365
dtype: float64
```

- *query()* method has been added that allows you to select elements of a DataFrame using a natural query syntax nearly identical to Python syntax. For example,

```
In [108]: n = 20

In [109]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=['a', 'b',
↪'c'])

In [110]: df.query('a < b < c')
Out[110]:
    a   b   c
11  1   5   8
15  8  16  19
```

  selects all the rows of df where a < b < c evaluates to True. For more details see the *the docs*.

- pd.read_msgpack() and pd.to_msgpack() are now a supported method of serialization of arbitrary pandas (and python objects) in a lightweight portable binary format. See *the docs*

> **Warning:** Since this is an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.

```
df = pd.DataFrame(np.random.rand(5, 2), columns=list('AB'))
df.to_msgpack('foo.msg')
pd.read_msgpack('foo.msg')

s = pd.Series(np.random.rand(5), index=pd.date_range('20130101', periods=5))
pd.to_msgpack('foo.msg', df, s)
pd.read_msgpack('foo.msg')
```

  You can pass iterator=True to iterator over the unpacked results

```
for o in pd.read_msgpack('foo.msg', iterator=True):
    print(o)
```

- pandas.io.gbq provides a simple way to extract from, and load data into, Google's BigQuery Data Sets by way of pandas DataFrames. BigQuery is a high performance SQL-like database service, useful for performing ad-hoc queries against extremely large datasets. *See the docs*

```
from pandas.io import gbq

# A query to select the average monthly temperatures in the
# in the year 2000 across the USA. The dataset,
# publicata:samples.gsod, is available on all BigQuery accounts,
# and is based on NOAA gsod data.

```

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```
query = """SELECT station_number as STATION,
month as MONTH, AVG(mean_temp) as MEAN_TEMP
FROM publicdata:samples.gsod
WHERE YEAR = 2000
GROUP BY STATION, MONTH
ORDER BY STATION, MONTH ASC"""

# Fetch the result set for this query

# Your Google BigQuery Project ID
# To find this, see your dashboard:
# https://console.developers.google.com/iam-admin/projects?authuser=0
projectid = 'xxxxxxxxx'
df = gbq.read_gbq(query, project_id=projectid)

# Use pandas to process and reshape the dataset

df2 = df.pivot(index='STATION', columns='MONTH', values='MEAN_TEMP')
df3 = pd.concat([df2.min(), df2.mean(), df2.max()],
                axis=1, keys=["Min Tem", "Mean Temp", "Max Temp"])
```

The resulting DataFrame is:

```
> df3
            Min Tem  Mean Temp    Max Temp
MONTH
1     -53.336667  39.827892   89.770968
2     -49.837500  43.685219   93.437932
3     -77.926087  48.708355   96.099998
4     -82.892858  55.070087   97.317240
5     -92.378261  61.428117  102.042856
6     -77.703334  65.858888  102.900000
7     -87.821428  68.169663  106.510714
8     -89.431999  68.614215  105.500000
9     -86.611112  63.436935  107.142856
10    -78.209677  56.880838   92.103333
11    -50.125000  48.861228   94.996428
12    -50.332258  42.286879   94.396774
```

Warning: To use this module, you will need a BigQuery account. See <https://cloud.google.com/products/big-query> for details.

As of 10/10/13, there is a bug in Google's API preventing result sets from being larger than 100,000 rows. A patch is scheduled for the week of 10/14/13.

Internal refactoring

In 0.13.0 there is a major refactor primarily to subclass `Series` from `NDFrame`, which is the base class currently for `DataFrame` and `Panel`, to unify methods and behaviors. Series formerly subclassed directly from `ndarray`. (GH4080, GH3862, GH816)

Warning: There are two potential incompatibilities from < 0.13.0

- Using certain numpy functions would previously return a `Series` if passed a `Series` as an argument. This seems only to affect `np.ones_like`, `np.empty_like`, `np.diff` and `np.where`. These now return `ndarrays`.

```
In [111]: s = pd.Series([1, 2, 3, 4])
```

Numpy Usage

```
In [112]: np.ones_like(s)
Out[112]: array([1, 1, 1, 1])

In [113]: np.diff(s)
Out[113]: array([1, 1, 1])

In [114]: np.where(s > 1, s, np.nan)
Out[114]: array([nan,  2.,  3.,  4.])
```

Pandonic Usage

```
In [115]: pd.Series(1, index=s.index)
Out[115]:
0    1
1    1
2    1
3    1
dtype: int64

In [116]: s.diff()
Out[116]:
0    NaN
1    1.0
2    1.0
3    1.0
dtype: float64

In [117]: s.where(s > 1)
Out[117]:
0    NaN
1    2.0
2    3.0
3    4.0
dtype: float64
```

- Passing a `Series` directly to a cython function expecting an `ndarray` type will no long work directly, you must pass `Series.values`, See *Enhancing Performance*
- `Series(0.5)` would previously return the scalar `0.5`, instead this will return a 1-element `Series`
- This change breaks `rpy2<=2.3.8`. an Issue has been opened against rpy2 and a workaround is detailed in GH5698. Thanks @JanSchulz.

- Pickle compatibility is preserved for pickles created prior to 0.13. These must be unpickled with `pd.`

`read_pickle`, see *Pickling*.

- Refactor of series.py/frame.py/panel.py to move common code to generic.py
  - added `_setup_axes` to created generic NDFrame structures
  - moved methods
    * `from_axes,_wrap_array,axes,ix,loc,iloc,shape,empty,swapaxes, transpose,pop`
    * `__iter__,keys,__contains__,__len__,__neg__,__invert__`
    * `convert_objects,as_blocks,as_matrix,values`
    * `__getstate__,__setstate__` (compat remains in frame/panel)
    * `__getattr__,__setattr__`
    * `_indexed_same,reindex_like,align,where,mask`
    * `fillna,replace` (`Series` replace is now consistent with `DataFrame`)
    * `filter` (also added axis argument to selectively filter on a different axis)
    * `reindex,reindex_axis,take`
    * `truncate` (moved to become part of `NDFrame`)
- These are API changes which make `Panel` more consistent with `DataFrame`
  - `swapaxes` on a `Panel` with the same axes specified now return a copy
  - support attribute access for setting
  - filter supports the same API as the original `DataFrame` filter
- Reindex called with no arguments will now return a copy of the input object
- `TimeSeries` is now an alias for `Series`. the property `is_time_series` can be used to distinguish (if desired)
- Refactor of Sparse objects to use BlockManager
  - Created a new block type in internals, `SparseBlock`, which can hold multi-dtypes and is non-consolidatable. `SparseSeries` and `SparseDataFrame` now inherit more methods from there hierarchy (Series/DataFrame), and no longer inherit from `SparseArray` (which instead is the object of the `SparseBlock`)
  - Sparse suite now supports integration with non-sparse data. Non-float sparse data is supportable (partially implemented)
  - Operations on sparse structures within DataFrames should preserve sparseness, merging type operations will convert to dense (and back to sparse), so might be somewhat inefficient
  - enable setitem on `SparseSeries` for boolean/integer/slices
  - `SparsePanels` implementation is unchanged (e.g. not using BlockManager, needs work)
- added `ftypes` method to Series/DataFrame, similar to `dtypes`, but indicates if the underlying is sparse/dense (as well as the dtype)
- All `NDFrame` objects can now use `__finalize__()` to specify various values to propagate to new objects from an existing one (e.g. `name` in `Series` will follow more automatically now)
- Internal type checking is now done via a suite of generated classes, allowing `isinstance(value, klass)` without having to directly import the klass, courtesy of @jtratner

- Bug in Series update where the parent frame is not updating its cache based on changes (GH4080) or types (GH3217), fillna (GH3386)
- Indexing with dtype conversions fixed (GH4463, GH4204)
- Refactor `Series.reindex` to core/generic.py (GH4604, GH4618), allow `method=` in reindexing on a Series to work
- `Series.copy` no longer accepts the `order` parameter and is now consistent with `NDFrame` copy
- Refactor `rename` methods to core/generic.py; fixes `Series.rename` for (GH4605), and adds `rename` with the same signature for `Panel`
- Refactor `clip` methods to core/generic.py (GH4798)
- Refactor of `_get_numeric_data/_get_bool_data` to core/generic.py, allowing Series/Panel functionality
- `Series` (for index) / `Panel` (for items) now allow attribute access to its elements (GH1903)

```
In [118]: s = pd.Series([1, 2, 3], index=list('abc'))

In [119]: s.b
Out[119]: 2

In [120]: s.a = 5

In [121]: s
Out[121]:
a    5
b    2
c    3
dtype: int64
```

Bug fixes

- `HDFStore`
  - raising an invalid `TypeError` rather than `ValueError` when appending with a different block ordering (GH4096)
  - `read_hdf` was not respecting as passed `mode` (GH4504)
  - appending a 0-len table will work correctly (GH4273)
  - `to_hdf` was raising when passing both arguments `append` and `table` (GH4584)
  - reading from a store with duplicate columns across dtypes would raise (GH4767)
  - Fixed a bug where `ValueError` wasn't correctly raised when column names weren't strings (GH4956)
  - A zero length series written in Fixed format not deserializing properly. (GH4708)
  - Fixed decoding perf issue on pyt3 (GH5441)
  - Validate levels in a MultiIndex before storing (GH5527)
  - Correctly handle `data_columns` with a Panel (GH5717)
- Fixed bug in tslib.tz_convert(vals, tz1, tz2): it could raise IndexError exception while trying to access trans[pos + 1] (GH4496)
- The `by` argument now works correctly with the `layout` argument (GH4102, GH4014) in `*.hist` plotting methods

- Fixed bug in `PeriodIndex.map` where using `str` would return the str representation of the index (GH4136)
- Fixed test failure `test_time_series_plot_color_with_empty_kwargs` when using custom matplotlib default colors (GH4345)
- Fix running of stata IO tests. Now uses temporary files to write (GH4353)
- Fixed an issue where `DataFrame.sum` was slower than `DataFrame.mean` for integer valued frames (GH4365)
- `read_html` tests now work with Python 2.6 (GH4351)
- Fixed bug where `network` testing was throwing `NameError` because a local variable was undefined (GH4381)
- In `to_json`, raise if a passed `orient` would cause loss of data because of a duplicate index (GH4359)
- In `to_json`, fix date handling so milliseconds are the default timestamp as the docstring says (GH4362).
- `as_index` is no longer ignored when doing groupby apply (GH4648, GH3417)
- JSON NaT handling fixed, NaTs are now serialized to `null` (GH4498)
- Fixed JSON handling of escapable characters in JSON object keys (GH4593)
- Fixed passing `keep_default_na=False` when `na_values=None` (GH4318)
- Fixed bug with `values` raising an error on a DataFrame with duplicate columns and mixed dtypes, surfaced in (GH4377)
- Fixed bug with duplicate columns and type conversion in `read_json` when `orient='split'` (GH4377)
- Fixed JSON bug where locales with decimal separators other than '.' threw exceptions when encoding / decoding certain values. (GH4918)
- Fix `.iat` indexing with a `PeriodIndex` (GH4390)
- Fixed an issue where `PeriodIndex` joining with self was returning a new instance rather than the same instance (GH4379); also adds a test for this for the other index types
- Fixed a bug with all the dtypes being converted to object when using the CSV cparser with the usecols parameter (GH3192)
- Fix an issue in merging blocks where the resulting DataFrame had partially set _ref_locs (GH4403)
- Fixed an issue where hist subplots were being overwritten when they were called using the top level matplotlib API (GH4408)
- Fixed a bug where calling `Series.astype(str)` would truncate the string (GH4405, GH4437)
- Fixed a py3 compat issue where bytes were being repr'd as tuples (GH4455)
- Fixed Panel attribute naming conflict if item is named 'a' (GH3440)
- Fixed an issue where duplicate indexes were raising when plotting (GH4486)
- Fixed an issue where cumsum and cumprod didn't work with bool dtypes (GH4170, GH4440)
- Fixed Panel slicing issued in `xs` that was returning an incorrect dimmed object (GH4016)
- Fix resampling bug where custom reduce function not used if only one group (GH3849, GH4494)
- Fixed Panel assignment with a transposed frame (GH3830)
- Raise on set indexing with a Panel and a Panel as a value which needs alignment (GH3777)
- frozenset objects now raise in the `Series` constructor (GH4482, GH4480)
- Fixed issue with sorting a duplicate MultiIndex that has multiple dtypes (GH4516)

- Fixed bug in `DataFrame.set_values` which was causing name attributes to be lost when expanding the index. (GH3742, GH4039)
- Fixed issue where individual `names`, `levels` and `labels` could be set on `MultiIndex` without validation (GH3714, GH4039)
- Fixed (GH3334) in pivot_table. Margins did not compute if values is the index.
- Fix bug in having a rhs of `np.timedelta64` or `np.offsets.DateOffset` when operating with datetimes (GH4532)
- Fix arithmetic with series/datetimeindex and `np.timedelta64` not working the same (GH4134) and buggy timedelta in NumPy 1.6 (GH4135)
- Fix bug in `pd.read_clipboard` on windows with PY3 (GH4561); not decoding properly
- `tslib.get_period_field()` and `tslib.get_period_field_arr()` now raise if code argument out of range (GH4519, GH4520)
- Fix boolean indexing on an empty series loses index names (GH4235), infer_dtype works with empty arrays.
- Fix reindexing with multiple axes; if an axes match was not replacing the current axes, leading to a possible lazy frequency inference issue (GH3317)
- Fixed issue where `DataFrame.apply` was reraising exceptions incorrectly (causing the original stack trace to be truncated).
- Fix selection with `ix/loc` and non_unique selectors (GH4619)
- Fix assignment with iloc/loc involving a dtype change in an existing column (GH4312, GH5702) have internal setitem_with_indexer in core/indexing to use Block.setitem
- Fixed bug where thousands operator was not handled correctly for floating point numbers in csv_import (GH4322)
- Fix an issue with CacheableOffset not properly being used by many DateOffset; this prevented the DateOffset from being cached (GH4609)
- Fix boolean comparison with a DataFrame on the lhs, and a list/tuple on the rhs (GH4576)
- Fix error/dtype conversion with setitem of `None` on `Series/DataFrame` (GH4667)
- Fix decoding based on a passed in non-default encoding in `pd.read_stata` (GH4626)
- Fix `DataFrame.from_records` with a plain-vanilla `ndarray`. (GH4727)
- Fix some inconsistencies with `Index.rename` and `MultiIndex.rename`, etc. (GH4718, GH4628)
- Bug in using `iloc/loc` with a cross-sectional and duplicate indices (GH4726)
- Bug with using `QUOTE_NONE` with `to_csv` causing `Exception`. (GH4328)
- Bug with Series indexing not raising an error when the right-hand-side has an incorrect length (GH2702)
- Bug in MultiIndexing with a partial string selection as one part of a MultIndex (GH4758)
- Bug with reindexing on the index with a non-unique index will now raise `ValueError` (GH4746)
- Bug in setting with `loc/ix` a single indexer with a MultiIndex axis and a NumPy array, related to (GH3777)
- Bug in concatenation with duplicate columns across dtypes not merging with axis=0 (GH4771, GH4975)
- Bug in `iloc` with a slice index failing (GH4771)
- Incorrect error message with no colspecs or width in `read_fwf`. (GH4774)
- Fix bugs in indexing in a Series with a duplicate index (GH4548, GH4550)

- Fixed bug with reading compressed files with `read_fwf` in Python 3. (GH3963)
- Fixed an issue with a duplicate index and assignment with a dtype change (GH4686)
- Fixed bug with reading compressed files in as `bytes` rather than `str` in Python 3. Simplifies bytes-producing file-handling in Python 3 (GH3963, GH4785).
- Fixed an issue related to ticklocs/ticklabels with log scale bar plots across different versions of matplotlib (GH4789)
- Suppressed DeprecationWarning associated with internal calls issued by repr() (GH4391)
- Fixed an issue with a duplicate index and duplicate selector with `.loc` (GH4825)
- Fixed an issue with `DataFrame.sort_index` where, when sorting by a single column and passing a list for `ascending`, the argument for `ascending` was being interpreted as `True` (GH4839, GH4846)
- Fixed `Panel.tshift` not working. Added `freq` support to `Panel.shift` (GH4853)
- Fix an issue in TextFileReader w/ Python engine (i.e. PythonParser) with thousands != "," (GH4596)
- Bug in getitem with a duplicate index when using where (GH4879)
- Fix Type inference code coerces float column into datetime (GH4601)
- Fixed `_ensure_numeric` does not check for complex numbers (GH4902)
- Fixed a bug in `Series.hist` where two figures were being created when the `by` argument was passed (GH4112, GH4113).
- Fixed a bug in `convert_objects` for > 2 ndims (GH4937)
- Fixed a bug in DataFrame/Panel cache insertion and subsequent indexing (GH4939, GH5424)
- Fixed string methods for `FrozenNDArray` and `FrozenList` (GH4929)
- Fixed a bug with setting invalid or out-of-range values in indexing enlargement scenarios (GH4940)
- Tests for fillna on empty Series (GH4346), thanks @immerrr
- Fixed `copy()` to shallow copy axes/indices as well and thereby keep separate metadata. (GH4202, GH4830)
- Fixed skiprows option in Python parser for read_csv (GH4382)
- Fixed bug preventing `cut` from working with `np.inf` levels without explicitly passing labels (GH3415)
- Fixed wrong check for overlapping in `DatetimeIndex.union` (GH4564)
- Fixed conflict between thousands separator and date parser in csv_parser (GH4678)
- Fix appending when dtypes are not the same (error showing mixing float/np.datetime64) (GH4993)
- Fix repr for DateOffset. No longer show duplicate entries in kwds. Removed unused offset fields. (GH4638)
- Fixed wrong index name during read_csv if using usecols. Applies to c parser only. (GH4201)
- `Timestamp` objects can now appear in the left hand side of a comparison operation with a `Series` or `DataFrame` object (GH4982).
- Fix a bug when indexing with `np.nan` via `iloc/loc` (GH5016)
- Fixed a bug where low memory c parser could create different types in different chunks of the same file. Now coerces to numerical type or raises warning. (GH3866)
- Fix a bug where reshaping a `Series` to its own shape raised `TypeError` (GH4554) and other reshaping issues.
- Bug in setting with `ix/loc` and a mixed int/string index (GH4544)

- Make sure series-series boolean comparisons are label based (GH4947)
- Bug in multi-level indexing with a Timestamp partial indexer (GH4294)
- Tests/fix for MultiIndex construction of an all-nan frame (GH4078)
- Fixed a bug where *read_html()* wasn't correctly inferring values of tables with commas (GH5029)
- Fixed a bug where *read_html()* wasn't providing a stable ordering of returned tables (GH4770, GH5029).
- Fixed a bug where *read_html()* was incorrectly parsing when passed `index_col=0` (GH5066).
- Fixed a bug where *read_html()* was incorrectly inferring the type of headers (GH5048).
- Fixed a bug where `DatetimeIndex` joins with `PeriodIndex` caused a stack overflow (GH3899).
- Fixed a bug where `groupby` objects didn't allow plots (GH5102).
- Fixed a bug where `groupby` objects weren't tab-completing column names (GH5102).
- Fixed a bug where `groupby.plot()` and friends were duplicating figures multiple times (GH5102).
- Provide automatic conversion of `object` dtypes on fillna, related (GH5103)
- Fixed a bug where default options were being overwritten in the option parser cleaning (GH5121).
- Treat a list/ndarray identically for `iloc` indexing with list-like (GH5006)
- Fix `MultiIndex.get_level_values()` with missing values (GH5074)
- Fix bound checking for Timestamp() with datetime64 input (GH4065)
- Fix a bug where `TestReadHtml` wasn't calling the correct `read_html()` function (GH5150).
- Fix a bug with `NDFrame.replace()` which made replacement appear as though it was (incorrectly) using regular expressions (GH5143).
- Fix better error message for to_datetime (GH4928)
- Made sure different locales are tested on travis-ci (GH4918). Also adds a couple of utilities for getting locales and setting locales with a context manager.
- Fixed segfault on `isnull(MultiIndex)` (now raises an error instead) (GH5123, GH5125)
- Allow duplicate indices when performing operations that align (GH5185, GH5639)
- Compound dtypes in a constructor raise `NotImplementedError` (GH5191)
- Bug in comparing duplicate frames (GH4421) related
- Bug in describe on duplicate frames
- Bug in `to_datetime` with a format and `coerce=True` not raising (GH5195)
- Bug in `loc` setting with multiple indexers and a rhs of a Series that needs broadcasting (GH5206)
- Fixed bug where inplace setting of levels or labels on `MultiIndex` would not clear cached `values` property and therefore return wrong `values`. (GH5215)
- Fixed bug where filtering a grouped DataFrame or Series did not maintain the original ordering (GH4621).
- Fixed `Period` with a business date freq to always roll-forward if on a non-business date. (GH5203)
- Fixed bug in Excel writers where frames with duplicate column names weren't written correctly. (GH5235)
- Fixed issue with `drop` and a non-unique index on Series (GH5248)
- Fixed segfault in C parser caused by passing more names than columns in the file. (GH5156)
- Fix `Series.isin` with date/time-like dtypes (GH5021)

- C and Python Parser can now handle the more common MultiIndex column format which doesn't have a row for index names (GH4702)
- Bug when trying to use an out-of-bounds date as an object dtype (GH5312)
- Bug when trying to display an embedded PandasObject (GH5324)
- Allows operating of Timestamps to return a datetime if the result is out-of-bounds related (GH5312)
- Fix return value/type signature of `initObjToJSON()` to be compatible with numpy's `import_array()` (GH5334, GH5326)
- Bug when renaming then set_index on a DataFrame (GH5344)
- Test suite no longer leaves around temporary files when testing graphics. (GH5347) (thanks for catching this @yarikoptic!)
- Fixed html tests on win32. (GH4580)
- Make sure that `head/tail` are `iloc` based, (GH5370)
- Fixed bug for `PeriodIndex` string representation if there are 1 or 2 elements. (GH5372)
- The GroupBy methods `transform` and `filter` can be used on Series and DataFrames that have repeated (non-unique) indices. (GH4620)
- Fix empty series not printing name in repr (GH4651)
- Make tests create temp files in temp directory by default. (GH5419)
- `pd.to_timedelta` of a scalar returns a scalar (GH5410)
- `pd.to_timedelta` accepts `NaN` and `NaT`, returning `NaT` instead of raising (GH5437)
- performance improvements in `isnull` on larger size pandas objects
- Fixed various setitem with 1d ndarray that does not have a matching length to the indexer (GH5508)
- Bug in getitem with a MultiIndex and `iloc` (GH5528)
- Bug in delitem on a Series (GH5542)
- Bug fix in apply when using custom function and objects are not mutated (GH5545)
- Bug in selecting from a non-unique index with `loc` (GH5553)
- Bug in groupby returning non-consistent types when user function returns a `None`, (GH5592)
- Work around regression in numpy 1.7.0 which erroneously raises IndexError from `ndarray.item` (GH5666)
- Bug in repeated indexing of object with resultant non-unique index (GH5678)
- Bug in fillna with Series and a passed series/dict (GH5703)
- Bug in groupby transform with a datetime-like grouper (GH5712)
- Bug in MultiIndex selection in PY3 when using certain keys (GH5725)
- Row-wise concat of differing dtypes failing in certain cases (GH5754)

Contributors

A total of 77 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.17 Version 0.12

5.17.1 Version 0.12.0 (July 24, 2013)

This is a major release from 0.11.0 and includes several new features and enhancements along with a large number of bug fixes.

Highlights include a consistent I/O API naming scheme, routines to read html, write MultiIndexes to csv files, read & write STATA data files, read & write JSON format files, Python 3 support for `HDFStore`, filtering of groupby expressions via `filter`, and a revamped `replace` routine that accepts regular expressions.

API changes

- The I/O API is now much more consistent with a set of top level `reader` functions accessed like `pd.read_csv()` that generally return a `pandas` object.
  - `read_csv`
  - `read_excel`
  - `read_hdf`
  - `read_sql`
  - `read_json`
  - `read_html`
  - `read_stata`
  - `read_clipboard`

  The corresponding `writer` functions are object methods that are accessed like `df.to_csv()`
  - `to_csv`
  - `to_excel`
  - `to_hdf`
  - `to_sql`
  - `to_json`
  - `to_html`
  - `to_stata`

  - to_clipboard

- Fix modulo and integer division on Series,DataFrames to act similarly to `float` dtypes to return `np.nan` or `np.inf` as appropriate (GH3590). This correct a numpy bug that treats `integer` and `float` dtypes differently.

```
In [1]: p = pd.DataFrame({"first": [4, 5, 8], "second": [0, 0, 3]})

In [2]: p % 0
Out[2]:
   first  second
0    NaN     NaN
1    NaN     NaN
2    NaN     NaN

In [3]: p % p
Out[3]:
   first  second
0    0.0     NaN
1    0.0     NaN
2    0.0     0.0

In [4]: p / p
Out[4]:
   first  second
0    1.0     NaN
1    1.0     NaN
2    1.0     1.0

In [5]: p / 0
Out[5]:
   first  second
0    inf     NaN
1    inf     NaN
2    inf     inf
```

- Add `squeeze` keyword to `groupby` to allow reduction from DataFrame -> Series if groups are unique. This is a Regression from 0.10.1. We are reverting back to the prior behavior. This means groupby will return the same shaped objects whether the groups are unique or not. Revert this issue (GH2893) with (GH3596).

```
In [2]: df2 = pd.DataFrame([{"val1": 1, "val2": 20},
   ...:                     {"val1": 1, "val2": 19},
   ...:                     {"val1": 1, "val2": 27},
   ...:                     {"val1": 1, "val2": 12}])

In [3]: def func(dataf):
   ...:     return dataf["val2"] - dataf["val2"].mean()
   ...:

In [4]: # squeezing the result frame to a series (because we have unique groups)
   ...: df2.groupby("val1", squeeze=True).apply(func)
Out[4]:
0    0.5
1   -0.5
2    7.5
3   -7.5
Name: 1, dtype: float64
```

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```
In [5]: # no squeezing (the default, and behavior in 0.10.1)
   ...: df2.groupby("val1").apply(func)
Out[5]:
val2    0    1    2    3
val1
1     0.5 -0.5  7.5 -7.5
```

- Raise on `iloc` when boolean indexing with a label based indexer mask e.g. a boolean Series, even with integer labels, will raise. Since `iloc` is purely positional based, the labels on the Series are not alignable (GH3631)

  This case is rarely used, and there are plenty of alternatives. This preserves the `iloc` API to be *purely* positional based.

```
In [6]: df = pd.DataFrame(range(5), index=list("ABCDE"), columns=["a"])

In [7]: mask = df.a % 2 == 0

In [8]: mask
Out[8]:
A     True
B    False
C     True
D    False
E     True
Name: a, dtype: bool

# this is what you should use
In [9]: df.loc[mask]
Out[9]:
   a
A  0
C  2
E  4

# this will work as well
In [10]: df.iloc[mask.values]
Out[10]:
   a
A  0
C  2
E  4
```

  `df.iloc[mask]` will raise a `ValueError`

- The `raise_on_error` argument to plotting functions is removed. Instead, plotting functions raise a `TypeError` when the `dtype` of the object is `object` to remind you to avoid `object` arrays whenever possible and thus you should cast to an appropriate numeric dtype if you need to plot something.
- Add `colormap` keyword to DataFrame plotting methods. Accepts either a matplotlib colormap object (ie, matplotlib.cm.jet) or a string name of such an object (ie, 'jet'). The colormap is sampled to select the color for each column. Please see *Colormaps* for more information. (GH3860)
- `DataFrame.interpolate()` is now deprecated. Please use `DataFrame.fillna()` and `DataFrame.replace()` instead. (GH3582, GH3675, GH3676)
- the `method` and `axis` arguments of `DataFrame.replace()` are deprecated
- `DataFrame.replace` 's `infer_types` parameter is removed and now performs conversion by default. (GH3907)

- Add the keyword `allow_duplicates` to `DataFrame.insert` to allow a duplicate column to be inserted if `True`, default is `False` (same as prior to 0.12) (GH3679)
- Implement `__nonzero__` for `NDFrame` objects (GH3691, GH3696)
- IO api
  - added top-level function `read_excel` to replace the following, The original API is deprecated and will be removed in a future version

```
from pandas.io.parsers import ExcelFile

xls = ExcelFile("path_to_file.xls")
xls.parse("Sheet1", index_col=None, na_values=["NA"])
```

    With

```
import pandas as pd

pd.read_excel("path_to_file.xls", "Sheet1", index_col=None, na_values=["NA"])
```

  - added top-level function `read_sql` that is equivalent to the following

```
from pandas.io.sql import read_frame

read_frame(...)
```

- `DataFrame.to_html` and `DataFrame.to_latex` now accept a path for their first argument (GH3702)
- Do not allow astypes on `datetime64[ns]` except to `object`, and `timedelta64[ns]` to `object/int` (GH3425)
- The behavior of `datetime64` dtypes has changed with respect to certain so-called reduction operations (GH3726). The following operations now raise a `TypeError` when performed on a `Series` and return an *empty* `Series` when performed on a `DataFrame` similar to performing these operations on, for example, a `DataFrame` of `slice` objects:
  - sum, prod, mean, std, var, skew, kurt, corr, and cov
- `read_html` now defaults to `None` when reading, and falls back on `bs4` + `html5lib` when lxml fails to parse. a list of parsers to try until success is also valid
- The internal `pandas` class hierarchy has changed (slightly). The previous `PandasObject` now is called `PandasContainer` and a new `PandasObject` has become the base class for `PandasContainer` as well as `Index`, `Categorical`, `GroupBy`, `SparseList`, and `SparseArray` (+ their base classes). Currently, `PandasObject` provides string methods (from `StringMixin`). (GH4090, GH4092)
- New `StringMixin` that, given a `__unicode__` method, gets python 2 and python 3 compatible string methods (`__str__`, `__bytes__`, and `__repr__`). Plus string safety throughout. Now employed in many places throughout the pandas library. (GH4090, GH4092)

IO enhancements

- `pd.read_html()` can now parse HTML strings, files or urls and return DataFrames, courtesy of @cpcloud. (GH3477, GH3605, GH3606, GH3616). It works with a *single* parser backend: BeautifulSoup4 + html5lib *See the docs*

  You can use `pd.read_html()` to read the output from `DataFrame.to_html()` like so

```
In [11]: df = pd.DataFrame({"a": range(3), "b": list("abc")})

In [12]: print(df)
   a  b
0  0  a
1  1  b
2  2  c

In [13]: html = df.to_html()

In [14]: alist = pd.read_html(html, index_col=0)

In [15]: print(df == alist[0])
      a     b
0  True  True
1  True  True
2  True  True
```

  Note that `alist` here is a Python `list` so `pd.read_html()` and `DataFrame.to_html()` are not inverses.

  - `pd.read_html()` no longer performs hard conversion of date strings (GH3656).

  Warning: You may have to install an older version of BeautifulSoup4, *See the installation docs*

- Added module for reading and writing Stata files: `pandas.io.stata` (GH1512) accessible via `read_stata` top-level function for reading, and `to_stata` DataFrame method for writing, *See the docs*
- Added module for reading and writing json format files: `pandas.io.json` accessible via `read_json` top-level function for reading, and `to_json` DataFrame method for writing, *See the docs* various issues (GH1226, GH3804, GH3876, GH3867, GH1305)
- `MultiIndex` column support for reading and writing csv format files
  - The `header` option in `read_csv` now accepts a list of the rows from which to read the index.
  - The option, `tupleize_cols` can now be specified in both `to_csv` and `read_csv`, to provide compatibility for the pre 0.12 behavior of writing and reading `MultIndex` columns via a list of tuples. The default in 0.12 is to write lists of tuples and *not* interpret list of tuples as a `MultiIndex` column.

    Note: The default behavior in 0.12 remains unchanged from prior versions, but starting with 0.13, the default *to* write and read `MultiIndex` columns will be in the new format. (GH3571, GH1651, GH3141)
  - If an `index_col` is not specified (e.g. you don't have an index, or wrote it with `df.to_csv(..., index=False)`, then any `names` on the columns index will be *lost*.

```
In [16]: from pandas._testing import makeCustomDataframe as mkdf

In [17]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)
```

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```
In [18]: df.to_csv("mi.csv")

In [19]: print(open("mi.csv").read())
C0,,C_l0_g0,C_l0_g1,C_l0_g2
C1,,C_l1_g0,C_l1_g1,C_l1_g2
C2,,C_l2_g0,C_l2_g1,C_l2_g2
C3,,C_l3_g0,C_l3_g1,C_l3_g2
R0,R1,,,
R_l0_g0,R_l1_g0,R0C0,R0C1,R0C2
R_l0_g1,R_l1_g1,R1C0,R1C1,R1C2
R_l0_g2,R_l1_g2,R2C0,R2C1,R2C2
R_l0_g3,R_l1_g3,R3C0,R3C1,R3C2
R_l0_g4,R_l1_g4,R4C0,R4C1,R4C2


In [20]: pd.read_csv("mi.csv", header=[0, 1, 2, 3], index_col=[0, 1])
Out[20]:
C0              C_l0_g0 C_l0_g1 C_l0_g2
C1              C_l1_g0 C_l1_g1 C_l1_g2
C2              C_l2_g0 C_l2_g1 C_l2_g2
C3              C_l3_g0 C_l3_g1 C_l3_g2
R0      R1
R_l0_g0 R_l1_g0    R0C0    R0C1    R0C2
R_l0_g1 R_l1_g1    R1C0    R1C1    R1C2
R_l0_g2 R_l1_g2    R2C0    R2C1    R2C2
R_l0_g3 R_l1_g3    R3C0    R3C1    R3C2
R_l0_g4 R_l1_g4    R4C0    R4C1    R4C2
```

- Support for `HDFStore` (via `PyTables 3.0.0`) on Python3
- Iterator support via `read_hdf` that automatically opens and closes the store when iteration is finished. This is only for *tables*

```
In [25]: path = 'store_iterator.h5'

In [26]: pd.DataFrame(np.random.randn(10, 2)).to_hdf(path, 'df', table=True)

In [27]: for df in pd.read_hdf(path, 'df', chunksize=3):
   ....:     print(df)
   ....:
          0         1
0  0.713216 -0.778461
1 -0.661062  0.862877
2  0.344342  0.149565
          0         1
3 -0.626968 -0.875772
4 -0.930687 -0.218983
5  0.949965 -0.442354
          0         1
6 -0.402985  1.111358
7 -0.241527 -0.670477
8  0.049355  0.632633
          0         1
9 -1.502767 -1.225492
```

- `read_csv` will now throw a more informative error message when a file contains no columns, e.g., all newline characters

Other enhancements

- `DataFrame.replace()` now allows regular expressions on contained `Series` with object dtype. See the examples section in the regular docs *Replacing via String Expression*

  For example you can do

```
In [21]: df = pd.DataFrame({"a": list("ab.."), "b": [1, 2, 3, 4]})

In [22]: df.replace(regex=r"\s*\.\s*", value=np.nan)
Out[22]:
     a  b
0    a  1
1    b  2
2  NaN  3
3  NaN  4
```

  to replace all occurrences of the string `'.'` with zero or more instances of surrounding white space with `NaN`.

  Regular string replacement still works as expected. For example, you can do

```
In [23]: df.replace(".", np.nan)
Out[23]:
     a  b
0    a  1
1    b  2
2  NaN  3
3  NaN  4
```

  to replace all occurrences of the string `'.'` with `NaN`.

- `pd.melt()` now accepts the optional parameters `var_name` and `value_name` to specify custom column names of the returned DataFrame.

- `pd.set_option()` now allows N option, value pairs (GH3667).

  Let's say that we had an option `'a.b'` and another option `'b.c'`. We can set them at the same time:

```
In [31]: pd.get_option('a.b')
Out[31]: 2

In [32]: pd.get_option('b.c')
Out[32]: 3

In [33]: pd.set_option('a.b', 1, 'b.c', 4)

In [34]: pd.get_option('a.b')
Out[34]: 1

In [35]: pd.get_option('b.c')
Out[35]: 4
```

- The `filter` method for group objects returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [24]: sf = pd.Series([1, 1, 2, 3, 3, 3])

In [25]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[25]:
```

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```
3    3
4    3
5    3
dtype: int64
```

The argument of `filter` must a function that, applied to the group as a whole, returns `True` or `False`.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [26]: dff = pd.DataFrame({"A": np.arange(8), "B": list("aabbbbcc")})

In [27]: dff.groupby("B").filter(lambda x: len(x) > 2)
Out[27]:
   A  B
2  2  b
3  3  b
4  4  b
5  5  b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [28]: dff.groupby("B").filter(lambda x: len(x) > 2, dropna=False)
Out[28]:
     A    B
0  NaN  NaN
1  NaN  NaN
2  2.0    b
3  3.0    b
4  4.0    b
5  5.0    b
6  NaN  NaN
7  NaN  NaN
```

- Series and DataFrame hist methods now take a `figsize` argument (GH3834)
- DatetimeIndexes no longer try to convert mixed-integer indexes during join operations (GH3877)
- Timestamp.min and Timestamp.max now represent valid Timestamp instances instead of the default datetime.min and datetime.max (respectively), thanks @SleepingPills
- `read_html` now raises when no tables are found and BeautifulSoup==4.2.0 is detected (GH4214)

Experimental features

- Added experimental `CustomBusinessDay` class to support `DateOffsets` with custom holiday calendars and custom weekmasks. (GH2301)

Note: This uses the `numpy.busdaycalendar` API introduced in Numpy 1.7 and therefore requires Numpy 1.7.0 or newer.

```
In [29]: from pandas.tseries.offsets import CustomBusinessDay

In [30]: from datetime import datetime
```

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```
# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
In [31]: weekmask_egypt = "Sun Mon Tue Wed Thu"

# They also observe International Workers' Day so let's
# add that for a couple of years
In [32]: holidays = ["2012-05-01", datetime(2013, 5, 1), np.datetime64("2014-05-01
↪")]

In [33]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_
↪egypt)

In [34]: dt = datetime(2013, 4, 30)

In [35]: print(dt + 2 * bday_egypt)
2013-05-05 00:00:00

In [36]: dts = pd.date_range(dt, periods=5, freq=bday_egypt)

In [37]: print(pd.Series(dts.weekday, dts).map(pd.Series("Mon Tue Wed Thu Fri Sat␣
↪Sun".split())))
2013-04-30    Tue
2013-05-02    Thu
2013-05-05    Sun
2013-05-06    Mon
2013-05-07    Tue
Freq: C, dtype: object
```

Bug fixes

- Plotting functions now raise a `TypeError` before trying to plot anything if the associated objects have a dtype of `object` (GH1818, GH3572, GH3911, GH3912), but they will try to convert object arrays to numeric arrays if possible so that you can still plot, for example, an object array with floats. This happens before any drawing takes place which eliminates any spurious plots from showing up.
- `fillna` methods now raise a `TypeError` if the `value` parameter is a list or tuple.
- `Series.str` now supports iteration (GH3638). You can iterate over the individual elements of each string in the `Series`. Each iteration yields a `Series` with either a single character at each index of the original `Series` or `NaN`. For example,

```
In [38]: strs = "go", "bow", "joe", "slow"

In [39]: ds = pd.Series(strs)

In [40]: for s in ds.str:
   ....:     print(s)
   ....:
0    g
1    b
2    j
3    s
dtype: object
0    o
1    o
```

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```
2    o
3    l
dtype: object
0    NaN
1      w
2      e
3      o
dtype: object
0    NaN
1    NaN
2    NaN
3      w
dtype: object

In [41]: s
Out[41]:
0    NaN
1    NaN
2    NaN
3      w
dtype: object

In [42]: s.dropna().values.item() == "w"
Out[42]: True
```

The last element yielded by the iterator will be a `Series` containing the last element of the longest string in the `Series` with all other elements being `NaN`. Here since `'slow'` is the longest string and there are no other strings with the same length `'w'` is the only non-null string in the yielded `Series`.

- `HDFStore`
  - will retain index attributes (freq,tz,name) on recreation (GH3499)
  - will warn with a `AttributeConflictWarning` if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
  - support datelike columns with a timezone as data_columns (GH2852)
- Non-unique index support clarified (GH3468).
  - Fix assigning a new index to a duplicate index in a DataFrame would fail (GH3468)
  - Fix construction of a DataFrame with a duplicate index
  - ref_locs support to allow duplicative indices across dtypes, allows iget support to always find the index (even across dtypes) (GH2194)
  - applymap on a DataFrame with a non-unique index now works (removed warning) (GH2786), and fix (GH3230)
  - Fix to_csv to handle non-unique columns (GH3495)
  - Duplicate indexes with getitem will return items in the correct order (GH3455, GH3457) and handle missing elements like unique indices (GH3561)
  - Duplicate indexes with and empty DataFrame.from_records will return a correct frame (GH3562)
  - Concat to produce a non-unique columns when duplicates are across dtypes is fixed (GH3602)
  - Allow insert/delete to non-unique columns (GH3679)

  - Non-unique indexing with a slice via `loc` and friends fixed (GH3659)
  - Allow insert/delete to non-unique columns (GH3679)
  - Extend `reindex` to correctly deal with non-unique indices (GH3679)
  - `DataFrame.itertuples()` now works with frames with duplicate column names (GH3873)
  - Bug in non-unique indexing via `iloc` (GH4017); added `takeable` argument to `reindex` for location-based taking
  - Allow non-unique indexing in series via `.ix/.loc` and `__getitem__` (GH4246)
  - Fixed non-unique indexing memory allocation issue with `.ix/.loc` (GH4280)
- `DataFrame.from_records` did not accept empty recarrays (GH3682)
- `read_html` now correctly skips tests (GH3741)
- Fixed a bug where `DataFrame.replace` with a compiled regular expression in the `to_replace` argument wasn't working (GH3907)
- Improved `network` test decorator to catch `IOError` (and therefore `URLError` as well). Added `with_connectivity_check` decorator to allow explicitly checking a website as a proxy for seeing if there is network connectivity. Plus, new `optional_args` decorator factory for decorators. (GH3910, GH3914)
- Fixed testing issue where too many sockets where open thus leading to a connection reset issue (GH3982, GH3985, GH4028, GH4054)
- Fixed failing tests in test_yahoo, test_google where symbols were not retrieved but were being accessed (GH3982, GH3985, GH4028, GH4054)
- `Series.hist` will now take the figure from the current environment if one is not passed
- Fixed bug where a 1xN DataFrame would barf on a 1xN mask (GH4071)
- Fixed running of `tox` under python3 where the pickle import was getting rewritten in an incompatible way (GH4062, GH4063)
- Fixed bug where sharex and sharey were not being passed to grouped_hist (GH4089)
- Fixed bug in `DataFrame.replace` where a nested dict wasn't being iterated over when regex=False (GH4115)
- Fixed bug in the parsing of microseconds when using the `format` argument in `to_datetime` (GH4152)
- Fixed bug in `PandasAutoDateLocator` where `invert_xaxis` triggered incorrectly `MilliSecondLocator` (GH3990)
- Fixed bug in plotting that wasn't raising on invalid colormap for matplotlib 1.1.1 (GH4215)
- Fixed the legend displaying in `DataFrame.plot(kind='kde')` (GH4216)
- Fixed bug where Index slices weren't carrying the name attribute (GH4226)
- Fixed bug in initializing `DatetimeIndex` with an array of strings in a certain time zone (GH4229)
- Fixed bug where html5lib wasn't being properly skipped (GH4265)
- Fixed bug where get_data_famafrench wasn't using the correct file edges (GH4281)

See the *full release notes* or issue tracker on GitHub for a complete list.

Contributors

A total of 50 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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5.18 Version 0.11

5.18.1 Version 0.11.0 (April 22, 2013)

This is a major release from 0.10.1 and includes many new features and enhancements along with a large number of bug fixes. The methods of Selecting Data have had quite a number of additions, and Dtype support is now full-fledged. There are also a number of important API changes that long-time pandas users should pay close attention to.

There is a new section in the documentation, *10 Minutes to Pandas*, primarily geared to new users.

There is a new section in the documentation, *Cookbook*, a collection of useful recipes in pandas (and that we want contributions!).

There are several libraries that are now *Recommended Dependencies*

Selection choices

Starting in 0.11.0, object selection has had a number of user-requested additions in order to support more explicit location based indexing. pandas now supports three types of multi-axis indexing.

- `.loc` is strictly label based, will raise `KeyError` when the items are not found, allowed inputs are:
  - A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index. This use is **not** an integer position along the index)
  - A list or array of labels `['a', 'b', 'c']`
  - A slice object with labels `'a':'f'`, (note that contrary to usual python slices, **both** the start and the stop are included!)

  - A boolean array

  See more at *Selection by Label*

- `.iloc` is strictly integer position based (from `0` to `length-1` of the axis), will raise `IndexError` when the requested indices are out of bounds. Allowed inputs are:

  - An integer e.g. `5`
  - A list or array of integers `[4, 3, 0]`
  - A slice object with ints `1:7`
  - A boolean array

  See more at *Selection by Position*

- `.ix` supports mixed integer and label based access. It is primarily label based, but will fallback to integer positional access. `.ix` is the most general and will support any of the inputs to `.loc` and `.iloc`, as well as support for floating point label schemes. `.ix` is especially useful when dealing with mixed positional and label based hierarchical indexes.

  As using integer slices with `.ix` have different behavior depending on whether the slice is interpreted as position based or label based, it's usually better to be explicit and use `.iloc` or `.loc`.

  See more at *Advanced Indexing* and *Advanced Hierarchical*.

Selection deprecations

Starting in version 0.11.0, these methods *may* be deprecated in future versions.

- `irow`
- `icol`
- `iget_value`

See the section *Selection by Position* for substitutes.

Dtypes

Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`, then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```
In [1]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')

In [2]: df1
Out[2]:
          A
0  0.469112
1 -0.282863
2 -1.509058
3 -1.135632
4  1.212112
5 -0.173215
6  0.119209
7 -1.044236

In [3]: df1.dtypes
```

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```
Out[3]:
A    float32
dtype: object

In [4]: df2 = pd.DataFrame({'A': pd.Series(np.random.randn(8), dtype='float16'),
   ...:                     'B': pd.Series(np.random.randn(8)),
   ...:                     'C': pd.Series(range(8), dtype='uint8')})
   ...:

In [5]: df2
Out[5]:
          A         B  C
0 -0.861816 -0.424972  0
1 -2.105469  0.567020  1
2 -0.494873  0.276232  2
3  1.072266 -1.087401  3
4  0.721680 -0.673690  4
5 -0.706543  0.113648  5
6 -1.040039 -1.478427  6
7  0.271973  0.524988  7

In [6]: df2.dtypes
Out[6]:
A    float16
B    float64
C      uint8
dtype: object

# here you get some upcasting
In [7]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [8]: df3
Out[8]:
          A         B    C
0 -0.392704 -0.424972  0.0
1 -2.388332  0.567020  1.0
2 -2.003932  0.276232  2.0
3 -0.063367 -1.087401  3.0
4  1.933792 -0.673690  4.0
5 -0.879758  0.113648  5.0
6 -0.920830 -1.478427  6.0
7 -0.772263  0.524988  7.0

In [9]: df3.dtypes
Out[9]:
A    float32
B    float64
C    float64
dtype: object
```

Dtype conversion

This is lower-common-denominator upcasting, meaning you get the dtype which can accommodate all of the types

```
In [10]: df3.values.dtype
Out[10]: dtype('float64')
```

Conversion

```
In [11]: df3.astype('float32').dtypes
Out[11]:
A    float32
B    float32
C    float32
dtype: object
```

Mixed conversion

```
In [12]: df3['D'] = '1.'

In [13]: df3['E'] = '1'

In [14]: df3.convert_objects(convert_numeric=True).dtypes
Out[14]:
A    float32
B    float64
C    float64
D    float64
E      int64
dtype: object

# same, but specific dtype conversion
In [15]: df3['D'] = df3['D'].astype('float16')

In [16]: df3['E'] = df3['E'].astype('int32')

In [17]: df3.dtypes
Out[17]:
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object
```

Forcing date coercion (and setting `NaT` when not datelike)

```
In [18]: import datetime

In [19]: s = pd.Series([datetime.datetime(2001, 1, 1, 0, 0), 'foo', 1.0, 1,
   ....:                pd.Timestamp('20010104'), '20010105'], dtype='O')
   ....:

In [20]: s.convert_objects(convert_dates='coerce')
Out[20]:
0   2001-01-01
1          NaT
2          NaT
```

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```
3          NaT
4   2001-01-04
5   2001-01-05
dtype: datetime64[ns]
```

Dtype gotchas

Platform gotchas

Starting in 0.11.0, construction of DataFrame/Series will use default dtypes of `int64` and `float64`, *regardless of platform*. This is not an apparent change from earlier versions of pandas. If you specify dtypes, they *WILL* be respected, however (GH2837)

The following will all result in `int64` dtypes

```
In [21]: pd.DataFrame([1, 2], columns=['a']).dtypes
Out[21]:
a    int64
dtype: object

In [22]: pd.DataFrame({'a': [1, 2]}).dtypes
Out[22]:
a    int64
dtype: object

In [23]: pd.DataFrame({'a': 1}, index=range(2)).dtypes
Out[23]:
a    int64
dtype: object
```

Keep in mind that `DataFrame(np.array([1,2]))` **WILL** result in `int32` on 32-bit platforms!

Upcasting gotchas

Performing indexing operations on integer type data can easily upcast the data. The dtype of the input data will be preserved in cases where `nans` are not introduced.

```
In [24]: dfi = df3.astype('int32')

In [25]: dfi['D'] = dfi['D'].astype('int64')

In [26]: dfi
Out[26]:
  A  B  C  D  E
0  0  0  0  1  1
1 -2  0  1  1  1
2 -2  0  2  1  1
3  0 -1  3  1  1
4  1  0  4  1  1
5  0  0  5  1  1
6  0 -1  6  1  1
7  0  0  7  1  1

In [27]: dfi.dtypes
Out[27]:
A    int32
```

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```
B    int32
C    int32
D    int64
E    int32
dtype: object

In [28]: casted = dfi[dfi > 0]

In [29]: casted
Out[29]:
    A   B    C  D  E
0 NaN NaN  NaN  1  1
1 NaN NaN  1.0  1  1
2 NaN NaN  2.0  1  1
3 NaN NaN  3.0  1  1
4 1.0 NaN  4.0  1  1
5 NaN NaN  5.0  1  1
6 NaN NaN  6.0  1  1
7 NaN NaN  7.0  1  1

In [30]: casted.dtypes
Out[30]:
A    float64
B    float64
C    float64
D      int64
E      int32
dtype: object
```

While float dtypes are unchanged.

```
In [31]: df4 = df3.copy()

In [32]: df4['A'] = df4['A'].astype('float32')

In [33]: df4.dtypes
Out[33]:
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object

In [34]: casted = df4[df4 > 0]

In [35]: casted
Out[35]:
          A         B    C    D  E
0       NaN       NaN  NaN  1.0  1
1       NaN  0.567020  1.0  1.0  1
2       NaN  0.276232  2.0  1.0  1
3       NaN       NaN  3.0  1.0  1
4  1.933792       NaN  4.0  1.0  1
5       NaN  0.113648  5.0  1.0  1
6       NaN       NaN  6.0  1.0  1
7       NaN  0.524988  7.0  1.0  1
```

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```
In [36]: casted.dtypes
Out[36]:
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object
```

Datetimes conversion

Datetime64[ns] columns in a DataFrame (or a Series) allow the use of `np.nan` to indicate a nan value, in addition to the traditional `NaT`, or not-a-time. This allows convenient nan setting in a generic way. Furthermore `datetime64[ns]` columns are created by default, when passed datetimelike objects (*this change was introduced in 0.10.1*) (GH2809, GH2810)

```
In [12]: df = pd.DataFrame(np.random.randn(6, 2), pd.date_range('20010102',␣
↪periods=6),
   ....:                   columns=['A', ' B'])
   ....:

In [13]: df['timestamp'] = pd.Timestamp('20010103')

In [14]: df
Out[14]:
                   A         B  timestamp
2001-01-02  0.404705  0.577046 2001-01-03
2001-01-03 -1.715002 -1.039268 2001-01-03
2001-01-04 -0.370647 -1.157892 2001-01-03
2001-01-05 -1.344312  0.844885 2001-01-03
2001-01-06  1.075770 -0.109050 2001-01-03
2001-01-07  1.643563 -1.469388 2001-01-03

# datetime64[ns] out of the box
In [15]: df.dtypes.value_counts()
Out[15]:
float64           2
datetime64[ns]    1
dtype: int64

# use the traditional nan, which is mapped to NaT internally
In [16]: df.loc[df.index[2:4], ['A', 'timestamp']] = np.nan

In [17]: df
Out[17]:
                   A         B  timestamp
2001-01-02  0.404705  0.577046 2001-01-03
2001-01-03 -1.715002 -1.039268 2001-01-03
2001-01-04       NaN -1.157892        NaT
2001-01-05       NaN  0.844885        NaT
2001-01-06  1.075770 -0.109050 2001-01-03
2001-01-07  1.643563 -1.469388 2001-01-03
```

Astype conversion on `datetime64[ns]` to `object`, implicitly converts `NaT` to `np.nan`

```
In [18]: s = pd.Series([datetime.datetime(2001, 1, 2, 0, 0) for i in range(3)])

In [19]: s.dtype
Out[19]: dtype('<M8[ns]')

In [20]: s[1] = np.nan

In [21]: s
Out[21]:
0   2001-01-02
1          NaT
2   2001-01-02
dtype: datetime64[ns]

In [22]: s.dtype
Out[22]: dtype('<M8[ns]')

In [23]: s = s.astype('O')

In [24]: s
Out[24]:
0    2001-01-02 00:00:00
1                    NaT
2    2001-01-02 00:00:00
dtype: object

In [25]: s.dtype
Out[25]: dtype('O')
```

API changes

- Added to_series() method to indices, to facilitate the creation of indexers (GH3275)
- `HDFStore`
  - added the method `select_column` to select a single column from a table as a Series.
  - deprecated the `unique` method, can be replicated by `select_column(key,column).unique()`
  - `min_itemsize` parameter to `append` will now automatically create data_columns for passed keys

Enhancements

- Improved performance of df.to_csv() by up to 10x in some cases. (GH3059)
- Numexpr is now a *Recommended Dependencies*, to accelerate certain types of numerical and boolean operations
- Bottleneck is now a *Recommended Dependencies*, to accelerate certain types of `nan` operations
- `HDFStore`
  - support `read_hdf/to_hdf` API similar to `read_csv/to_csv`

```
In [26]: df = pd.DataFrame({'A': range(5), 'B': range(5)})

In [27]: df.to_hdf('store.h5', 'table', append=True)

In [28]: pd.read_hdf('store.h5', 'table', where=['index > 2'])
```

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```
Out[28]:
   A  B
3  3  3
4  4  4
```

  - provide dotted attribute access to `get` from stores, e.g. `store.df == store['df']`
  - new keywords `iterator=boolean`, and `chunksize=number_in_a_chunk` are provided to support iteration on `select` and `select_as_multiple` (GH3076)

- You can now select timestamps from an *unordered* timeseries similarly to an *ordered* timeseries (GH2437)
- You can now select with a string from a DataFrame with a datelike index, in a similar way to a Series (GH3070)

```
In [29]: idx = pd.date_range("2001-10-1", periods=5, freq='M')

In [30]: ts = pd.Series(np.random.rand(len(idx)), index=idx)

In [31]: ts['2001']
Out[31]:
2001-10-31    0.117967
2001-11-30    0.702184
2001-12-31    0.414034
Freq: M, dtype: float64

In [32]: df = pd.DataFrame({'A': ts})

In [33]: df['2001']
Out[33]:
                   A
2001-10-31  0.117967
2001-11-30  0.702184
2001-12-31  0.414034
```

- `Squeeze` to possibly remove length 1 dimensions from an object.

```
>>> p = pd.Panel(np.random.randn(3, 4, 4), items=['ItemA', 'ItemB', 'ItemC'],
...              major_axis=pd.date_range('20010102', periods=4),
...              minor_axis=['A', 'B', 'C', 'D'])
>>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2001-01-02 00:00:00 to 2001-01-05 00:00:00
Minor_axis axis: A to D

>>> p.reindex(items=['ItemA']).squeeze()
                   A         B         C         D
2001-01-02  0.926089 -2.026458  0.501277 -0.204683
2001-01-03 -0.076524  1.081161  1.141361  0.479243
2001-01-04  0.641817 -0.185352  1.824568  0.809152
2001-01-05  0.575237  0.669934  1.398014 -0.399338

>>> p.reindex(items=['ItemA'], minor=['B']).squeeze()
2001-01-02   -2.026458
2001-01-03    1.081161
2001-01-04   -0.185352
```

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```
2001-01-05    0.669934
Freq: D, Name: B, dtype: float64
```

- In `pd.io.data.Options`,
  - Fix bug when trying to fetch data for the current month when already past expiry.
  - Now using lxml to scrape html instead of BeautifulSoup (lxml was faster).
  - New instance variables for calls and puts are automatically created when a method that creates them is called. This works for current month where the instance variables are simply `calls` and `puts`. Also works for future expiry months and save the instance variable as `callsMMYY` or `putsMMYY`, where `MMYY` are, respectively, the month and year of the option's expiry.
  - `Options.get_near_stock_price` now allows the user to specify the month for which to get relevant options data.
  - `Options.get_forward_data` now has optional kwargs `near` and `above_below`. This allows the user to specify if they would like to only return forward looking data for options near the current stock price. This just obtains the data from Options.get_near_stock_price instead of Options.get_xxx_data() (GH2758).
- Cursor coordinate information is now displayed in time-series plots.
- added option `display.max_seq_items` to control the number of elements printed per sequence pprinting it. (GH2979)
- added option `display.chop_threshold` to control display of small numerical values. (GH2739)
- added option `display.max_info_rows` to prevent verbose_info from being calculated for frames above 1M rows (configurable). (GH2807, GH2918)
- value_counts() now accepts a "normalize" argument, for normalized histograms. (GH2710).
- DataFrame.from_records now accepts not only dicts but any instance of the collections.Mapping ABC.
- added option `display.mpl_style` providing a sleeker visual style for plots. Based on https://gist.github.com/huyng/816622 (GH3075).
- Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)
- to_html() now accepts an optional "escape" argument to control reserved HTML character escaping (enabled by default) and escapes `&`, in addition to < and >. (GH2919)

See the *full release notes* or issue tracker on GitHub for a complete list.

Contributors

A total of 50 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Adam Greenhall +
- Alvaro Tejero-Cantero +
- Andy Hayden
- Brad Buran +
- Chang She
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- Chris Withers +
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5.19 Version 0.10

5.19.1 Version 0.10.1 (January 22, 2013)

This is a minor release from 0.10.0 and includes new features, enhancements, and bug fixes. In particular, there is substantial new HDFStore functionality contributed by Jeff Reback.

An undesired API breakage with functions taking the `inplace` option has been reverted and deprecation warnings added.

API changes

- Functions taking an `inplace` option return the calling object as before. A deprecation message has been added
- Groupby aggregations Max/Min no longer exclude non-numeric data (GH2700)
- Resampling an empty DataFrame now returns an empty DataFrame instead of raising an exception (GH2640)
- The file reader will now raise an exception when NA values are found in an explicitly specified integer column instead of converting the column to float (GH2631)
- DatetimeIndex.unique now returns a DatetimeIndex with the same name and
- timezone instead of an array (GH2563)

New features

- MySQL support for database (contribution from Dan Allan)

HDFStore

You may need to upgrade your existing data files. Please visit the **compatibility** section in the main docs.

You can designate (and index) certain columns that you want to be able to perform queries on a table, by passing a list to `data_columns`

```
In [1]: store = pd.HDFStore("store.h5")

In [2]: df = pd.DataFrame(
   ...:     np.random.randn(8, 3),
   ...:     index=pd.date_range("1/1/2000", periods=8),
```

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```
   ...:     columns=["A", "B", "C"],
   ...: )
   ...:

In [3]: df["string"] = "foo"

In [4]: df.loc[df.index[4:6], "string"] = np.nan

In [5]: df.loc[df.index[7:9], "string"] = "bar"

In [6]: df["string2"] = "cool"

In [7]: df
Out[7]:
                   A         B         C string string2
2000-01-01  0.469112 -0.282863 -1.509059    foo    cool
2000-01-02 -1.135632  1.212112 -0.173215    foo    cool
2000-01-03  0.119209 -1.044236 -0.861849    foo    cool
2000-01-04 -2.104569 -0.494929  1.071804    foo    cool
2000-01-05  0.721555 -0.706771 -1.039575    NaN    cool
2000-01-06  0.271860 -0.424972  0.567020    NaN    cool
2000-01-07  0.276232 -1.087401 -0.673690    foo    cool
2000-01-08  0.113648 -1.478427  0.524988    bar    cool

# on-disk operations
In [8]: store.append("df", df, data_columns=["B", "C", "string", "string2"])

In [9]: store.select("df", "B>0 and string=='foo'")
Out[9]:
                   A         B         C string string2
2000-01-02 -1.135632  1.212112 -0.173215    foo    cool

# this is in-memory version of this type of selection
In [10]: df[(df.B > 0) & (df.string == "foo")]
Out[10]:
                   A         B         C string string2
2000-01-02 -1.135632  1.212112 -0.173215    foo    cool
```

Retrieving unique values in an indexable or data column.

```
# note that this is deprecated as of 0.14.0
# can be replicated by: store.select_column('df','index').unique()
store.unique("df", "index")
store.unique("df", "string")
```

You can now store `datetime64` in data columns

```
In [11]: df_mixed = df.copy()

In [12]: df_mixed["datetime64"] = pd.Timestamp("20010102")

In [13]: df_mixed.loc[df_mixed.index[3:4], ["A", "B"]] = np.nan

In [14]: store.append("df_mixed", df_mixed)

In [15]: df_mixed1 = store.select("df_mixed")
```

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```
In [16]: df_mixed1
Out[16]:
                   A         B         C string string2 datetime64
2000-01-01  0.469112 -0.282863 -1.509059    foo    cool 2001-01-02
2000-01-02 -1.135632  1.212112 -0.173215    foo    cool 2001-01-02
2000-01-03  0.119209 -1.044236 -0.861849    foo    cool 2001-01-02
2000-01-04       NaN       NaN  1.071804    foo    cool 2001-01-02
2000-01-05  0.721555 -0.706771 -1.039575    NaN    cool 2001-01-02
2000-01-06  0.271860 -0.424972  0.567020    NaN    cool 2001-01-02
2000-01-07  0.276232 -1.087401 -0.673690    foo    cool 2001-01-02
2000-01-08  0.113648 -1.478427  0.524988    bar    cool 2001-01-02

In [17]: df_mixed1.dtypes.value_counts()
Out[17]:
float64           3
object            2
datetime64[ns]    1
dtype: int64
```

You can pass `columns` keyword to select to filter a list of the return columns, this is equivalent to passing a `Term('columns',list_of_columns_to_filter)`

```
In [18]: store.select("df", columns=["A", "B"])
Out[18]:
                   A         B
2000-01-01  0.469112 -0.282863
2000-01-02 -1.135632  1.212112
2000-01-03  0.119209 -1.044236
2000-01-04 -2.104569 -0.494929
2000-01-05  0.721555 -0.706771
2000-01-06  0.271860 -0.424972
2000-01-07  0.276232 -1.087401
2000-01-08  0.113648 -1.478427
```

`HDFStore` now serializes MultiIndex dataframes when appending tables.

```
In [19]: index = pd.MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'],
   ....:                               ['one', 'two', 'three']],
   ....:                       labels=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
   ....:                               [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
   ....:                       names=['foo', 'bar'])
   ....:

In [20]: df = pd.DataFrame(np.random.randn(10, 3), index=index,
   ....:                   columns=['A', 'B', 'C'])
   ....:

In [21]: df
Out[21]:
                A         B         C
foo bar
foo one    -0.116619  0.295575 -1.047704
    two     1.640556  1.905836  2.772115
    three   0.088787 -1.144197 -0.633372
bar one     0.925372 -0.006438 -0.820408
    two    -0.600874 -1.039266  0.824758
```

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```
baz two   -0.824095 -0.337730 -0.927764
    three -0.840123  0.248505 -0.109250
qux one    0.431977 -0.460710  0.336505
    two   -3.207595 -1.535854  0.409769
    three -0.673145 -0.741113 -0.110891

In [22]: store.append('mi', df)

In [23]: store.select('mi')
Out[23]:
                  A         B         C
foo bar
foo one   -0.116619  0.295575 -1.047704
    two    1.640556  1.905836  2.772115
    three  0.088787 -1.144197 -0.633372
bar one    0.925372 -0.006438 -0.820408
    two   -0.600874 -1.039266  0.824758
baz two   -0.824095 -0.337730 -0.927764
    three -0.840123  0.248505 -0.109250
qux one    0.431977 -0.460710  0.336505
    two   -3.207595 -1.535854  0.409769
    three -0.673145 -0.741113 -0.110891

# the levels are automatically included as data columns
In [24]: store.select('mi', "foo='bar'")
Out[24]:
                A         B         C
foo bar
bar one  0.925372 -0.006438 -0.820408
    two -0.600874 -1.039266  0.824758
```

Multi-table creation via `append_to_multiple` and selection via `select_as_multiple` can create/select from multiple tables and return a combined result, by using `where` on a selector table.

```
In [19]: df_mt = pd.DataFrame(
   ....:     np.random.randn(8, 6),
   ....:     index=pd.date_range("1/1/2000", periods=8),
   ....:     columns=["A", "B", "C", "D", "E", "F"],
   ....: )
   ....:

In [20]: df_mt["foo"] = "bar"

# you can also create the tables individually
In [21]: store.append_to_multiple(
   ....:     {"df1_mt": ["A", "B"], "df2_mt": None}, df_mt, selector="df1_mt"
   ....: )
   ....:

In [22]: store
Out[22]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# individual tables were created
In [23]: store.select("df1_mt")
```

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```
Out[23]:
                   A         B
2000-01-01  0.404705  0.577046
2000-01-02 -1.344312  0.844885
2000-01-03  0.357021 -0.674600
2000-01-04  0.276662 -0.472035
2000-01-05  0.895717  0.805244
2000-01-06 -1.170299 -0.226169
2000-01-07 -0.076467 -1.187678
2000-01-08  1.024180  0.569605

In [24]: store.select("df2_mt")
Out[24]:
                   C         D         E         F  foo
2000-01-01 -1.715002 -1.039268 -0.370647 -1.157892  bar
2000-01-02  1.075770 -0.109050  1.643563 -1.469388  bar
2000-01-03 -1.776904 -0.968914 -1.294524  0.413738  bar
2000-01-04 -0.013960 -0.362543 -0.006154 -0.923061  bar
2000-01-05 -1.206412  2.565646  1.431256  1.340309  bar
2000-01-06  0.410835  0.813850  0.132003 -0.827317  bar
2000-01-07  1.130127 -1.436737 -1.413681  1.607920  bar
2000-01-08  0.875906 -2.211372  0.974466 -2.006747  bar

# as a multiple
In [25]: store.select_as_multiple(
   ....:     ["df1_mt", "df2_mt"], where=["A>0", "B>0"], selector="df1_mt"
   ....: )
   ....:
Out[25]:
                   A         B         C         D         E         F  foo
2000-01-01  0.404705  0.577046 -1.715002 -1.039268 -0.370647 -1.157892  bar
2000-01-05  0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309  bar
2000-01-08  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747  bar
```

Enhancements

- `HDFStore` now can read native PyTables table format tables
- You can pass `nan_rep = 'my_nan_rep'` to append, to change the default nan representation on disk (which converts to/from `np.nan`), this defaults to `nan`.
- You can pass `index` to `append`. This defaults to `True`. This will automagically create indices on the *indexables* and *data columns* of the table
- You can pass `chunksize=an integer` to `append`, to change the writing chunksize (default is 50000). This will significantly lower your memory usage on writing.
- You can pass `expectedrows=an integer` to the first `append`, to set the TOTAL number of expected rows that `PyTables` will expected. This will optimize read/write performance.
- `Select` now supports passing `start` and `stop` to provide selection space limiting in selection.
- Greatly improved ISO8601 (e.g., yyyy-mm-dd) date parsing for file parsers (GH2698)
- Allow `DataFrame.merge` to handle combinatorial sizes too large for 64-bit integer (GH2690)
- Series now has unary negation (-series) and inversion (~series) operators (GH2686)
- DataFrame.plot now includes a `logx` parameter to change the x-axis to log scale (GH2327)
- Series arithmetic operators can now handle constant and ndarray input (GH2574)

- ExcelFile now takes a `kind` argument to specify the file type (GH2613)
- A faster implementation for Series.str methods (GH2602)

Bug Fixes

- `HDFStore` tables can now store `float32` types correctly (cannot be mixed with `float64` however)
- Fixed Google Analytics prefix when specifying request segment (GH2713).
- Function to reset Google Analytics token store so users can recover from improperly setup client secrets (GH2687).
- Fixed groupby bug resulting in segfault when passing in MultiIndex (GH2706)
- Fixed bug where passing a Series with datetime64 values into `to_datetime` results in bogus output values (GH2699)
- Fixed bug in `pattern in HDFStore` expressions when pattern is not a valid regex (GH2694)
- Fixed performance issues while aggregating boolean data (GH2692)
- When given a boolean mask key and a Series of new values, Series __setitem__ will now align the incoming values with the original Series (GH2686)
- Fixed MemoryError caused by performing counting sort on sorting MultiIndex levels with a very large number of combinatorial values (GH2684)
- Fixed bug that causes plotting to fail when the index is a DatetimeIndex with a fixed-offset timezone (GH2683)
- Corrected business day subtraction logic when the offset is more than 5 bdays and the starting date is on a weekend (GH2680)
- Fixed C file parser behavior when the file has more columns than data (GH2668)
- Fixed file reader bug that misaligned columns with data in the presence of an implicit column and a specified `usecols` value
- DataFrames with numerical or datetime indices are now sorted prior to plotting (GH2609)
- Fixed DataFrame.from_records error when passed columns, index, but empty records (GH2633)
- Several bug fixed for Series operations when dtype is datetime64 (GH2689, GH2629, GH2626)

See the *full release notes* or issue tracker on GitHub for a complete list.

Contributors

A total of 17 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Andy Hayden +
- Anton I. Sipos +
- Chang She
- Christopher Whelan
- Damien Garaud +
- Dan Allan +
- Dieter Vandenbussche
- Garrett Drapala +

- Jay Parlar +
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- Vincent Arel-Bundock +
- Wes McKinney
- elpres
- herrfz +
- jreback
- svaksha +
- y-p

5.19.2 Version 0.10.0 (December 17, 2012)

This is a major release from 0.9.1 and includes many new features and enhancements along with a large number of bug fixes. There are also a number of important API changes that long-time pandas users should pay close attention to.

File parsing new features

The delimited file parsing engine (the guts of `read_csv` and `read_table`) has been rewritten from the ground up and now uses a fraction the amount of memory while parsing, while being 40% or more faster in most use cases (in some cases much faster).

There are also many new features:

- Much-improved Unicode handling via the `encoding` option.
- Column filtering (`usecols`)
- Dtype specification (`dtype` argument)
- Ability to specify strings to be recognized as True/False
- Ability to yield NumPy record arrays (`as_recarray`)
- High performance `delim_whitespace` option
- Decimal format (e.g. European format) specification
- Easier CSV dialect options: `escapechar`, `lineterminator`, `quotechar`, etc.
- More robust handling of many exceptional kinds of files observed in the wild

API changes

Deprecated DataFrame BINOP TimeSeries special case behavior

The default behavior of binary operations between a DataFrame and a Series has always been to align on the DataFrame's columns and broadcast down the rows, **except** in the special case that the DataFrame contains time series. Since there are now method for each binary operator enabling you to specify how you want to broadcast, we are phasing out this special case (Zen of Python: *Special cases aren't special enough to break the rules*). Here's what I'm talking about:

```
In [1]: import pandas as pd

In [2]: df = pd.DataFrame(np.random.randn(6, 4), index=pd.date_range("1/1/2000",␣
↪periods=6))

In [3]: df
Out[3]:
                   0         1         2         3
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988

# deprecated now
In [4]: df - df[0]
Out[4]:
            2000-01-01 00:00:00  2000-01-02 00:00:00  2000-01-03 00:00:00  2000-01-04␣
↪00:00:00  ...   0   1   2   3
2000-01-01                  NaN                  NaN                  NaN           ␣
↪     NaN  ... NaN NaN NaN NaN
2000-01-02                  NaN                  NaN                  NaN           ␣
↪     NaN  ... NaN NaN NaN NaN
2000-01-03                  NaN                  NaN                  NaN           ␣
↪     NaN  ... NaN NaN NaN NaN
2000-01-04                  NaN                  NaN                  NaN           ␣
↪     NaN  ... NaN NaN NaN NaN
2000-01-05                  NaN                  NaN                  NaN           ␣
↪     NaN  ... NaN NaN NaN NaN
2000-01-06                  NaN                  NaN                  NaN           ␣
↪     NaN  ... NaN NaN NaN NaN

[6 rows x 10 columns]

# Change your code to
In [5]: df.sub(df[0], axis=0)  # align on axis 0 (rows)
Out[5]:
              0         1         2         3
2000-01-01  0.0 -0.751976 -1.978171 -1.604745
2000-01-02  0.0 -1.385327 -1.092903 -2.256348
2000-01-03  0.0 -1.242720  0.366920  1.933653
2000-01-04  0.0 -1.428326 -1.761130 -0.449695
2000-01-05  0.0  0.991993  0.701204 -0.662428
2000-01-06  0.0  0.787338 -0.804737  1.198677
```

You will get a deprecation warning in the 0.10.x series, and the deprecated functionality will be removed in 0.11 or later.

Altered resample default behavior

The default time series `resample` binning behavior of daily `D` and *higher* frequencies has been changed to `closed='left', label='left'`. Lower nfrequencies are unaffected. The prior defaults were causing a great deal of confusion for users, especially resampling data to daily frequency (which labeled the aggregated group with the end of the interval: the next day).

```
In [1]: dates = pd.date_range('1/1/2000', '1/5/2000', freq='4h')
```

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```
In [2]: series = pd.Series(np.arange(len(dates)), index=dates)

In [3]: series
Out[3]:
2000-01-01 00:00:00     0
2000-01-01 04:00:00     1
2000-01-01 08:00:00     2
2000-01-01 12:00:00     3
2000-01-01 16:00:00     4
2000-01-01 20:00:00     5
2000-01-02 00:00:00     6
2000-01-02 04:00:00     7
2000-01-02 08:00:00     8
2000-01-02 12:00:00     9
2000-01-02 16:00:00    10
2000-01-02 20:00:00    11
2000-01-03 00:00:00    12
2000-01-03 04:00:00    13
2000-01-03 08:00:00    14
2000-01-03 12:00:00    15
2000-01-03 16:00:00    16
2000-01-03 20:00:00    17
2000-01-04 00:00:00    18
2000-01-04 04:00:00    19
2000-01-04 08:00:00    20
2000-01-04 12:00:00    21
2000-01-04 16:00:00    22
2000-01-04 20:00:00    23
2000-01-05 00:00:00    24
Freq: 4H, dtype: int64

In [4]: series.resample('D', how='sum')
Out[4]:
2000-01-01     15
2000-01-02     51
2000-01-03     87
2000-01-04    123
2000-01-05     24
Freq: D, dtype: int64

In [5]: # old behavior
In [6]: series.resample('D', how='sum', closed='right', label='right')
Out[6]:
2000-01-01      0
2000-01-02     21
2000-01-03     57
2000-01-04     93
2000-01-05    129
Freq: D, dtype: int64
```

- Infinity and negative infinity are no longer treated as NA by `isnull` and `notnull`. That they ever were was a relic of early pandas. This behavior can be re-enabled globally by the `mode.use_inf_as_null` option:

```
In [6]: s = pd.Series([1.5, np.inf, 3.4, -np.inf])

In [7]: pd.isnull(s)
```

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```
Out[7]:
0    False
1    False
2    False
3    False
Length: 4, dtype: bool

In [8]: s.fillna(0)
Out[8]:
0    1.500000
1         inf
2    3.400000
3        -inf
Length: 4, dtype: float64

In [9]: pd.set_option('use_inf_as_null', True)

In [10]: pd.isnull(s)
Out[10]:
0    False
1     True
2    False
3     True
Length: 4, dtype: bool

In [11]: s.fillna(0)
Out[11]:
0    1.5
1    0.0
2    3.4
3    0.0
Length: 4, dtype: float64

In [12]: pd.reset_option('use_inf_as_null')
```

- Methods with the `inplace` option now all return `None` instead of the calling object. E.g. code written like `df = df.fillna(0, inplace=True)` may stop working. To fix, simply delete the unnecessary variable assignment.
- `pandas.merge` no longer sorts the group keys (`sort=False`) by default. This was done for performance reasons: the group-key sorting is often one of the more expensive parts of the computation and is often unnecessary.
- The default column names for a file with no header have been changed to the integers `0` through `N - 1`. This is to create consistency with the DataFrame constructor with no columns specified. The v0.9.0 behavior (names `X0`, `X1`, ...) can be reproduced by specifying `prefix='X'`:

```
In [6]: import io

In [7]: data = """
   ...: a,b,c
   ...: 1,Yes,2
   ...: 3,No,4
   ...: """
   ...:

In [8]: print(data)
```

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```
a,b,c
1,Yes,2
3,No,4


In [9]: pd.read_csv(io.StringIO(data), header=None)
Out[9]:
   0    1  2
0  a    b  c
1  1  Yes  2
2  3   No  4

In [10]: pd.read_csv(io.StringIO(data), header=None, prefix="X")
Out[10]:
  X0   X1 X2
0  a    b  c
1  1  Yes  2
2  3   No  4
```

- Values like `'Yes'` and `'No'` are not interpreted as boolean by default, though this can be controlled by new `true_values` and `false_values` arguments:

```
In [11]: print(data)

a,b,c
1,Yes,2
3,No,4


In [12]: pd.read_csv(io.StringIO(data))
Out[12]:
   a    b  c
0  1  Yes  2
1  3   No  4

In [13]: pd.read_csv(io.StringIO(data), true_values=["Yes"], false_values=["No"])
Out[13]:
   a      b  c
0  1   True  2
1  3  False  4
```

- The file parsers will not recognize non-string values arising from a converter function as NA if passed in the `na_values` argument. It's better to do post-processing using the `replace` function instead.
- Calling `fillna` on Series or DataFrame with no arguments is no longer valid code. You must either specify a fill value or an interpolation method:

```
In [14]: s = pd.Series([np.nan, 1.0, 2.0, np.nan, 4])

In [15]: s
Out[15]:
0    NaN
1    1.0
2    2.0
3    NaN
4    4.0
```

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```
dtype: float64

In [16]: s.fillna(0)
Out[16]:
0    0.0
1    1.0
2    2.0
3    0.0
4    4.0
dtype: float64

In [17]: s.fillna(method="pad")
Out[17]:
0    NaN
1    1.0
2    2.0
3    2.0
4    4.0
dtype: float64
```

Convenience methods `ffill` and `bfill` have been added:

```
In [18]: s.ffill()
Out[18]:
0    NaN
1    1.0
2    2.0
3    2.0
4    4.0
dtype: float64
```

- `Series.apply` will now operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame

```
In [19]: def f(x):
   ....:     return pd.Series([x, x ** 2], index=["x", "x^2"])
   ....:

In [20]: s = pd.Series(np.random.rand(5))

In [21]: s
Out[21]:
0    0.340445
1    0.984729
2    0.919540
3    0.037772
4    0.861549
dtype: float64

In [22]: s.apply(f)
Out[22]:
          x       x^2
0  0.340445  0.115903
1  0.984729  0.969691
2  0.919540  0.845555
3  0.037772  0.001427
4  0.861549  0.742267
```

- New API functions for working with pandas options (GH2097):
  - `get_option` / `set_option` - get/set the value of an option. Partial names are accepted. - `reset_option` - reset one or more options to their default value. Partial names are accepted. - `describe_option` - print a description of one or more options. When called with no arguments. print all registered options.

  Note: `set_printoptions`/ `reset_printoptions` are now deprecated (but functioning), the print options now live under "display.XYZ". For example:

```
In [23]: pd.get_option("display.max_rows")
Out[23]: 15
```

- to_string() methods now always return unicode strings (GH2224).

New features

Wide DataFrame printing

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```
In [24]: wide_frame = pd.DataFrame(np.random.randn(5, 16))

In [25]: wide_frame
Out[25]:
          0         1         2         3         4         5   ...         10
↪11        12        13        14        15
0 -0.548702  1.467327 -1.015962 -0.483075  1.637550 -1.217659  ... -0.919069  0.
↪266046 -0.709661  1.669052  1.037882 -1.705775
1 -0.919854 -0.042379  1.247642 -0.009920  0.290213  0.495767  ...  0.337863 -0.
↪945867 -0.932132  1.956030  0.017587 -0.016692
2 -0.575247  0.254161 -1.143704  0.215897  1.193555 -0.077118  ...  1.627081 -0.
↪990582 -0.441652  1.211526  0.268520  0.024580
3 -1.577585  0.396823 -0.105381 -0.532532  1.453749  1.208843  ...  0.339969 -0.
↪693205 -0.339355  0.593616  0.884345  1.591431
4  0.141809  0.220390  0.435589  0.192451 -0.096701  0.803351  ...  1.018601 -0.
↪595447  1.395433 -0.392670  0.007207  1.928123

[5 rows x 16 columns]
```

The old behavior of printing out summary information can be achieved via the 'expand_frame_repr' print option:

```
In [26]: pd.set_option("expand_frame_repr", False)

In [27]: wide_frame
Out[27]:
          0         1         2         3         4         5         6         7
↪    8         9         10        11        12        13        14        15
0 -0.548702  1.467327 -1.015962 -0.483075  1.637550 -1.217659 -0.291519 -1.745505 -0.
↪263952  0.991460 -0.919069  0.266046 -0.709661  1.669052  1.037882 -1.705775
1 -0.919854 -0.042379  1.247642 -0.009920  0.290213  0.495767  0.362949  1.548106 -1.
↪131345 -0.089329  0.337863 -0.945867 -0.932132  1.956030  0.017587 -0.016692
2 -0.575247  0.254161 -1.143704  0.215897  1.193555 -0.077118 -0.408530 -0.862495  1.
↪346061  1.511763  1.627081 -0.990582 -0.441652  1.211526  0.268520  0.024580
3 -1.577585  0.396823 -0.105381 -0.532532  1.453749  1.208843 -0.080952 -0.264610 -0.
↪727965 -0.589346  0.339969 -0.693205 -0.339355  0.593616  0.884345  1.591431
```

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```
4  0.141809  0.220390  0.435589  0.192451 -0.096701  0.803351  1.715071 -0.708758 -1.
↪202872 -1.814470  1.018601 -0.595447  1.395433 -0.392670  0.007207  1.928123
```

The width of each line can be changed via 'line_width' (80 by default):

```
pd.set_option("line_width", 40)

wide_frame
```

Updated PyTables support

Docs for PyTables `Table` format & several enhancements to the api. Here is a taste of what to expect.

```
In [41]: store = pd.HDFStore('store.h5')

In [42]: df = pd.DataFrame(np.random.randn(8, 3),
   ....:                   index=pd.date_range('1/1/2000', periods=8),
   ....:                   columns=['A', 'B', 'C'])

In [43]: df
Out[43]:
                   A         B         C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376

[8 rows x 3 columns]

# appending data frames
In [44]: df1 = df[0:4]

In [45]: df2 = df[4:]

In [46]: store.append('df', df1)

In [47]: store.append('df', df2)

In [48]: store
Out[48]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df            frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])

# selecting the entire store
In [49]: store.select('df')
Out[49]:
                   A         B         C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
```

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```
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376

[8 rows x 3 columns]
```

```
In [50]: wp = pd.Panel(np.random.randn(2, 5, 4), items=['Item1', 'Item2'],
   ....:               major_axis=pd.date_range('1/1/2000', periods=5),
   ....:               minor_axis=['A', 'B', 'C', 'D'])

In [51]: wp
Out[51]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

# storing a panel
In [52]: store.append('wp', wp)

# selecting via A QUERY
In [53]: store.select('wp', [pd.Term('major_axis>20000102'),
   ....:                     pd.Term('minor_axis', '=', ['A', 'B'])])
   ....:
Out[53]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to B

# removing data from tables
In [54]: store.remove('wp', pd.Term('major_axis>20000103'))
Out[54]: 8

In [55]: store.select('wp')
Out[55]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to D

# deleting a store
In [56]: del store['df']

In [57]: store
Out[57]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/wp            wide_table   (typ->appendable,nrows->12,ncols->2,indexers->[major_axis,
↪minor_axis])
```

Enhancements

- added ability to hierarchical keys

```
In [58]: store.put('foo/bar/bah', df)

In [59]: store.append('food/orange', df)

In [60]: store.append('food/apple', df)

In [61]: store
Out[61]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah            frame        (shape->[8,3])
/food/apple             frame_table  (typ->appendable,nrows->8,ncols->3,
↪indexers->[index])
/food/orange            frame_table  (typ->appendable,nrows->8,ncols->3,
↪indexers->[index])
/wp                     wide_table   (typ->appendable,nrows->12,ncols->2,
↪indexers->[major_axis,minor_axis])

# remove all nodes under this level
In [62]: store.remove('food')

In [63]: store
Out[63]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah            frame        (shape->[8,3])
/wp                     wide_table   (typ->appendable,nrows->12,ncols->2,
↪indexers->[major_axis,minor_axis])
```

- added mixed-dtype support!

```
In [64]: df['string'] = 'string'

In [65]: df['int'] = 1

In [66]: store.append('df', df)

In [67]: df1 = store.select('df')

In [68]: df1
Out[68]:
                   A         B         C  string  int
2000-01-01 -2.036047  0.000830 -0.955697  string    1
2000-01-02 -0.898872 -0.725411  0.059904  string    1
2000-01-03 -0.449644  1.082900 -1.221265  string    1
2000-01-04  0.361078  1.330704  0.855932  string    1
2000-01-05 -1.216718  1.488887  0.018993  string    1
2000-01-06 -0.877046  0.045976  0.437274  string    1
2000-01-07 -0.567182 -0.888657 -0.556383  string    1
2000-01-08  0.655457  1.117949 -2.782376  string    1

[8 rows x 5 columns]

In [69]: df1.get_dtype_counts()
Out[69]:
float64    3
```

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```
int64      1
object     1
dtype: int64
```

- performance improvements on table writing
- support for arbitrarily indexed dimensions
- `SparseSeries` now has a `density` property (GH2384)
- enable `Series.str.strip/lstrip/rstrip` methods to take an input argument to strip arbitrary characters (GH2411)
- implement `value_vars` in `melt` to limit values to certain columns and add `melt` to pandas namespace (GH2412)

Bug Fixes

- added `Term` method of specifying where conditions (GH1996).
- `del store['df']` now call `store.remove('df')` for store deletion
- deleting of consecutive rows is much faster than before
- `min_itemsize` parameter can be specified in table creation to force a minimum size for indexing columns (the previous implementation would set the column size based on the first append)
- indexing support via `create_table_index` (requires PyTables >= 2.3) (GH698).
- appending on a store would fail if the table was not first created via `put`
- fixed issue with missing attributes after loading a pickled dataframe (GH2431)
- minor change to select and remove: require a table ONLY if where is also provided (and not None)

Compatibility

0.10 of `HDFStore` is backwards compatible for reading tables created in a prior version of pandas, however, query terms using the prior (undocumented) methodology are unsupported. You must read in the entire file and write it out using the new format to take advantage of the updates.

N dimensional panels (experimental)

Adding experimental support for Panel4D and factory functions to create n-dimensional named panels. Here is a taste of what to expect.

```
In [58]: p4d = Panel4D(np.random.randn(2, 2, 5, 4),
   ....:       labels=['Label1','Label2'],
   ....:       items=['Item1', 'Item2'],
   ....:       major_axis=date_range('1/1/2000', periods=5),
   ....:       minor_axis=['A', 'B', 'C', 'D'])
   ....:

In [59]: p4d
Out[59]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

See the *full release notes* or issue tracker on GitHub for a complete list.

Contributors

A total of 26 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- A. Flaxman +
- Abraham Flaxman
- Adam Obeng +
- Brenda Moon +
- Chang She
- Chris Mulligan +
- Dieter Vandenbussche
- Donald Curtis +
- Jay Bourque +
- Jeff Reback +
- Justin C Johnson +
- K.-Michael Aye
- Keith Hughitt +
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- Luke Lee +
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- locojaydev +
- timmie
- y-p
- zach powers +

5.20 Version 0.9

5.20.1 Version 0.9.1 (November 14, 2012)

This is a bug fix release from 0.9.0 and includes several new features and enhancements along with a large number of bug fixes. The new features include by-column sort order for DataFrame and Series, improved NA handling for the rank method, masking functions for DataFrame, and intraday time-series filtering for DataFrame.

New features

- `Series.sort`, `DataFrame.sort`, and `DataFrame.sort_index` can now be specified in a per-column manner to support multiple sort orders (GH928)

```
In [2]: df = pd.DataFrame(np.random.randint(0, 2, (6, 3)),
   ...:                   columns=['A', 'B', 'C'])

In [3]: df.sort(['A', 'B'], ascending=[1, 0])

Out[3]:
   A  B  C
3  0  1  1
4  0  1  1
2  0  0  1
0  1  0  0
1  1  0  0
5  1  0  0
```

- `DataFrame.rank` now supports additional argument values for the `na_option` parameter so missing values can be assigned either the largest or the smallest rank (GH1508, GH2159)

```
In [1]: df = pd.DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])

In [2]: df.loc[2:4] = np.nan

In [3]: df.rank()
Out[3]:
     A    B    C
0  3.0  2.0  1.0
1  1.0  3.0  2.0
2  NaN  NaN  NaN
3  NaN  NaN  NaN
4  NaN  NaN  NaN
5  2.0  1.0  3.0

[6 rows x 3 columns]

In [4]: df.rank(na_option='top')
Out[4]:
     A    B    C
0  6.0  5.0  4.0
1  4.0  6.0  5.0
2  2.0  2.0  2.0
3  2.0  2.0  2.0
4  2.0  2.0  2.0
5  5.0  4.0  6.0
```

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```
[6 rows x 3 columns]

In [5]: df.rank(na_option='bottom')
Out[5]:
     A    B    C
0  3.0  2.0  1.0
1  1.0  3.0  2.0
2  5.0  5.0  5.0
3  5.0  5.0  5.0
4  5.0  5.0  5.0
5  2.0  1.0  3.0

[6 rows x 3 columns]
```

- DataFrame has new `where` and `mask` methods to select values according to a given boolean mask (GH2109, GH2151)

  DataFrame currently supports slicing via a boolean vector the same length as the DataFrame (inside the `[]`). The returned DataFrame has the same number of columns as the original, but is sliced on its index.

```
In [6]: df = DataFrame(np.random.randn(5, 3), columns = ['A','B','C'])

In [7]: df
Out[7]:
          A         B         C
0  0.276232 -1.087401 -0.673690
1  0.113648 -1.478427  0.524988
2  0.404705  0.577046 -1.715002
3 -1.039268 -0.370647 -1.157892
4 -1.344312  0.844885  1.075770

[5 rows x 3 columns]

In [8]: df[df['A'] > 0]
Out[8]:
          A         B         C
0  0.276232 -1.087401 -0.673690
1  0.113648 -1.478427  0.524988
2  0.404705  0.577046 -1.715002

[3 rows x 3 columns]
```

  If a DataFrame is sliced with a DataFrame based boolean condition (with the same size as the original DataFrame), then a DataFrame the same size (index and columns) as the original is returned, with elements that do not meet the boolean condition as `NaN`. This is accomplished via the new method `DataFrame.where`. In addition, `where` takes an optional `other` argument for replacement.

```
In [9]: df[df>0]
Out[9]:
          A         B         C
0  0.276232       NaN       NaN
1  0.113648       NaN  0.524988
2  0.404705  0.577046       NaN
```

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```
3       NaN       NaN       NaN
4       NaN  0.844885  1.075770

[5 rows x 3 columns]

In [10]: df.where(df>0)
Out[10]:
          A         B         C
0  0.276232       NaN       NaN
1  0.113648       NaN  0.524988
2  0.404705  0.577046       NaN
3       NaN       NaN       NaN
4       NaN  0.844885  1.075770

[5 rows x 3 columns]

In [11]: df.where(df>0,-df)
Out[11]:
          A         B         C
0  0.276232  1.087401  0.673690
1  0.113648  1.478427  0.524988
2  0.404705  0.577046  1.715002
3  1.039268  0.370647  1.157892
4  1.344312  0.844885  1.075770

[5 rows x 3 columns]
```

Furthermore, `where` now aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.ix` (but on the contents rather than the axis labels)

```
In [12]: df2 = df.copy()

In [13]: df2[ df2[1:4] > 0 ] = 3

In [14]: df2
Out[14]:
          A         B         C
0  0.276232 -1.087401 -0.673690
1  3.000000 -1.478427  3.000000
2  3.000000  3.000000 -1.715002
3 -1.039268 -0.370647 -1.157892
4 -1.344312  0.844885  1.075770

[5 rows x 3 columns]
```

`DataFrame.mask` is the inverse boolean operation of `where`.

```
In [15]: df.mask(df<=0)
Out[15]:
          A         B         C
0  0.276232       NaN       NaN
1  0.113648       NaN  0.524988
2  0.404705  0.577046       NaN
3       NaN       NaN       NaN
4       NaN  0.844885  1.075770
```

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```
[5 rows x 3 columns]
```

- Enable referencing of Excel columns by their column names (GH1936)

```
In [16]: xl = pd.ExcelFile('data/test.xls')

In [17]: xl.parse('Sheet1', index_col=0, parse_dates=True,
   ....:          parse_cols='A:D')
   ....:
Out[17]:
                   A         B         C         D
2000-01-03  0.980269  3.685731 -0.364217 -1.159738
2000-01-04  1.047916 -0.041232 -0.161812  0.212549
2000-01-05  0.498581  0.731168 -0.537677  1.346270
2000-01-06  1.120202  1.567621  0.003641  0.675253
2000-01-07 -0.487094  0.571455 -1.611639  0.103469
2000-01-10  0.836649  0.246462  0.588543  1.062782
2000-01-11 -0.157161  1.340307  1.195778 -1.097007

[7 rows x 4 columns]
```

- Added option to disable pandas-style tick locators and formatters using `series.plot(x_compat=True)` or `pandas.plot_params['x_compat'] = True` (GH2205)
- Existing TimeSeries methods `at_time` and `between_time` were added to DataFrame (GH2149)
- DataFrame.dot can now accept ndarrays (GH2042)
- DataFrame.drop now supports non-unique indexes (GH2101)
- Panel.shift now supports negative periods (GH2164)
- DataFrame now support unary ~ operator (GH2110)

API changes

- Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

```
In [1]: prng = pd.period_range('2012Q1', periods=2, freq='Q')

In [2]: s = pd.Series(np.random.randn(len(prng)), prng)

In [4]: s.resample('M')
Out[4]:
2012-01   -1.471992
2012-02         NaN
2012-03         NaN
2012-04   -0.493593
2012-05         NaN
2012-06         NaN
Freq: M, dtype: float64
```

- Period.end_time now returns the last nanosecond in the time interval (GH2124, GH2125, GH1764)

```
In [18]: p = pd.Period('2012')

In [19]: p.end_time
Out[19]: Timestamp('2012-12-31 23:59:59.999999999')
```

- File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)

```
In [20]: import io

In [21]: data = ('A,B,C\n'
   ....:         '00001,001,5\n'
   ....:         '00002,002,6')
   ....:

In [22]: pd.read_csv(io.StringIO(data), converters={'A': lambda x: x.strip()})
Out[22]:
       A  B  C
0  00001  1  5
1  00002  2  6

[2 rows x 3 columns]
```

See the *full release notes* or issue tracker on GitHub for a complete list.

Contributors

A total of 11 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Brenda Moon +
- Chang She
- Jeff Reback +
- Justin C Johnson +
- K.-Michael Aye
- Martin Blais
- Tobias Brandt +
- Wes McKinney
- Wouter Overmeire
- timmie
- y-p

5.20.2 Version 0.9.0 (October 7, 2012)

This is a major release from 0.8.1 and includes several new features and enhancements along with a large number of bug fixes. New features include vectorized unicode encoding/decoding for `Series.str`, `to_latex` method to DataFrame, more flexible parsing of boolean values, and enabling the download of options data from Yahoo! Finance.

New features

- Add `encode` and `decode` for unicode handling to *vectorized string processing methods* in Series.str (GH1706)
- Add `DataFrame.to_latex` method (GH1735)
- Add convenient expanding window equivalents of all rolling_* ops (GH1785)
- Add Options class to pandas.io.data for fetching options data from Yahoo! Finance (GH1748, GH1739)
- More flexible parsing of boolean values (Yes, No, TRUE, FALSE, etc) (GH1691, GH1295)
- Add `level` parameter to `Series.reset_index`
- `TimeSeries.between_time` can now select times across midnight (GH1871)
- Series constructor can now handle generator as input (GH1679)
- `DataFrame.dropna` can now take multiple axes (tuple/list) as input (GH924)
- Enable `skip_footer` parameter in `ExcelFile.parse` (GH1843)

API changes

- The default column names when `header=None` and no columns names passed to functions like `read_csv` has changed to be more Pythonic and amenable to attribute access:

```
In [1]: import io

In [2]: data = """
   ...: 0,0,1
   ...: 1,1,0
   ...: 0,1,0
   ...: """
   ...:

In [3]: df = pd.read_csv(io.StringIO(data), header=None)

In [4]: df
Out[4]:
   0  1  2
0  0  0  1
1  1  1  0
2  0  1  0

[3 rows x 3 columns]
```

- Creating a Series from another Series, passing an index, will cause reindexing to happen inside rather than treating the Series like an ndarray. Technically improper usages like `Series(df[col1], index=df[col2])` that worked before "by accident" (this was never intended) will lead to all NA Series in some cases. To be perfectly clear:

```
In [5]: s1 = pd.Series([1, 2, 3])

In [6]: s1
Out[6]:
0    1
1    2
2    3
Length: 3, dtype: int64

In [7]: s2 = pd.Series(s1, index=["foo", "bar", "baz"])

In [8]: s2
Out[8]:
foo   NaN
bar   NaN
baz   NaN
Length: 3, dtype: float64
```

- Deprecated `day_of_year` API removed from PeriodIndex, use `dayofyear` (GH1723)
- Don't modify NumPy suppress printoption to True at import time
- The internal HDF5 data arrangement for DataFrames has been transposed. Legacy files will still be readable by HDFStore (GH1834, GH1824)
- Legacy cruft removed: pandas.stats.misc.quantileTS
- Use ISO8601 format for Period repr: monthly, daily, and on down (GH1776)
- Empty DataFrame columns are now created as object dtype. This will prevent a class of TypeErrors that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) (GH1783)
- Setting parts of DataFrame/Panel using ix now aligns input Series/DataFrame (GH1630)
- `first` and `last` methods in `GroupBy` no longer drop non-numeric columns (GH1809)
- Resolved inconsistencies in specifying custom NA values in text parser. `na_values` of type dict no longer override default NAs unless `keep_default_na` is set to false explicitly (GH1657)
- `DataFrame.dot` will not do data alignment, and also work with Series (GH1915)

See the *full release notes* or issue tracker on GitHub for a complete list.

Contributors

A total of 24 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

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- Christopher Whelan +
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- Johnny +
- Joshua Leahy +
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- Martin Blais
- MinRK +
- Paul Ivanov +
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- Yaroslav Halchenko
- lenolib +
- tshauck +
- y-p +
- Øystein S. Haaland +

5.21 Version 0.8

5.21.1 Version 0.8.1 (July 22, 2012)

This release includes a few new features, performance enhancements, and over 30 bug fixes from 0.8.0. New features include notably NA friendly string processing functionality and a series of new plot types and options.

New features

- Add *vectorized string processing methods* accessible via Series.str (GH620)
- Add option to disable adjustment in EWMA (GH1584)
- *Radviz plot* (GH1566)
- *Parallel coordinates plot*
- *Bootstrap plot*
- Per column styles and secondary y-axis plotting (GH1559)
- New datetime converters millisecond plotting (GH1599)
- Add option to disable "sparse" display of hierarchical indexes (GH1538)
- Series/DataFrame's `set_index` method can *append levels* to an existing Index/MultiIndex (GH1569, GH1577)

Performance improvements

- Improved implementation of rolling min and max (thanks to Bottleneck !)
- Add accelerated `'median'` GroupBy option (GH1358)
- Significantly improve the performance of parsing ISO8601-format date strings with `DatetimeIndex` or `to_datetime` (GH1571)
- Improve the performance of GroupBy on single-key aggregations and use with Categorical types
- Significant datetime parsing performance improvements

Contributors

A total of 5 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Chang She
- Skipper Seabold
- Todd DeLuca +
- Vytautas Jancauskas
- Wes McKinney

5.21.2 Version 0.8.0 (June 29, 2012)

This is a major release from 0.7.3 and includes extensive work on the time series handling and processing infrastructure as well as a great deal of new functionality throughout the library. It includes over 700 commits from more than 20 distinct authors. Most pandas 0.7.3 and earlier users should not experience any issues upgrading, but due to the migration to the NumPy datetime64 dtype, there may be a number of bugs and incompatibilities lurking. Lingering incompatibilities will be fixed ASAP in a 0.8.1 release if necessary. See the *full release notes* or issue tracker on GitHub for a complete list.

Support for non-unique indexes

All objects can now work with non-unique indexes. Data alignment / join operations work according to SQL join semantics (including, if application, index duplication in many-to-many joins)

NumPy datetime64 dtype and 1.6 dependency

Time series data are now represented using NumPy's datetime64 dtype; thus, pandas 0.8.0 now requires at least NumPy 1.6. It has been tested and verified to work with the development version (1.7+) of NumPy as well which includes some significant user-facing API changes. NumPy 1.6 also has a number of bugs having to do with nanosecond resolution data, so I recommend that you steer clear of NumPy 1.6's datetime64 API functions (though limited as they are) and only interact with this data using the interface that pandas provides.

See the end of the 0.8.0 section for a "porting" guide listing potential issues for users migrating legacy code bases from pandas 0.7 or earlier to 0.8.0.

Bug fixes to the 0.7.x series for legacy NumPy < 1.6 users will be provided as they arise. There will be no more further development in 0.7.x beyond bug fixes.

Time Series changes and improvements

Note: With this release, legacy scikits.timeseries users should be able to port their code to use pandas.

Note: See *documentation* for overview of pandas timeseries API.

- New datetime64 representation **speeds up join operations and data alignment**, **reduces memory usage**, and improve serialization / deserialization performance significantly over datetime.datetime
- High performance and flexible **resample** method for converting from high-to-low and low-to-high frequency. Supports interpolation, user-defined aggregation functions, and control over how the intervals and result labeling are defined. A suite of high performance Cython/C-based resampling functions (including Open-High-Low-Close) have also been implemented.
- Revamp of *frequency aliases* and support for **frequency shortcuts** like '15min', or '1h30min'
- New *DatetimeIndex class* supports both fixed frequency and irregular time series. Replaces now deprecated DateRange class
- New `PeriodIndex` and `Period` classes for representing *time spans* and performing **calendar logic**, including the `12 fiscal quarterly frequencies <timeseries.quarterly>`. This is a partial port of, and a substantial enhancement to, elements of the scikits.timeseries code base. Support for conversion between PeriodIndex and DatetimeIndex
- New Timestamp data type subclasses `datetime.datetime`, providing the same interface while enabling working with nanosecond-resolution data. Also provides *easy time zone conversions*.
- Enhanced support for *time zones*. Add `tz_convert` and `tz_localize` methods to TimeSeries and DataFrame. All timestamps are stored as UTC; Timestamps from DatetimeIndex objects with time zone set will be localized to local time. Time zone conversions are therefore essentially free. User needs to know very little about pytz library now; only time zone names as strings are required. Time zone-aware timestamps are equal if and only if their UTC timestamps match. Operations between time zone-aware time series with different time zones will result in a UTC-indexed time series.
- Time series **string indexing conveniences** / shortcuts: slice years, year and month, and index values with strings
- Enhanced time series **plotting**; adaptation of scikits.timeseries matplotlib-based plotting code
- New `date_range`, `bdate_range`, and `period_range` *factory functions*
- Robust **frequency inference** function `infer_freq` and `inferred_freq` property of DatetimeIndex, with option to infer frequency on construction of DatetimeIndex
- to_datetime function efficiently **parses array of strings** to DatetimeIndex. DatetimeIndex will parse array or list of strings to datetime64
- **Optimized** support for datetime64-dtype data in Series and DataFrame columns
- New NaT (Not-a-Time) type to represent **NA** in timestamp arrays
- Optimize Series.asof for looking up **"as of" values** for arrays of timestamps
- Milli, Micro, Nano date offset objects
- Can index time series with datetime.time objects to select all data at particular **time of day** (`TimeSeries.at_time`) or **between two times** (`TimeSeries.between_time`)
- Add *tshift* method for leading/lagging using the frequency (if any) of the index, as opposed to a naive lead/lag using shift

Other new features

- New *cut* and `qcut` functions (like R's cut function) for computing a categorical variable from a continuous variable by binning values either into value-based (`cut`) or quantile-based (`qcut`) bins
- Rename `Factor` to `Categorical` and add a number of usability features
- Add *limit* argument to fillna/reindex
- More flexible multiple function application in GroupBy, and can pass list (name, function) tuples to get result in particular order with given names
- Add flexible *replace* method for efficiently substituting values
- Enhanced *read_csv/read_table* for reading time series data and converting multiple columns to dates
- Add *comments* option to parser functions: read_csv, etc.
- Add *dayfirst* option to parser functions for parsing international DD/MM/YYYY dates
- Allow the user to specify the CSV reader *dialect* to control quoting etc.
- Handling *thousands* separators in read_csv to improve integer parsing.
- Enable unstacking of multiple levels in one shot. Alleviate `pivot_table` bugs (empty columns being introduced)
- Move to klib-based hash tables for indexing; better performance and less memory usage than Python's dict
- Add first, last, min, max, and prod optimized GroupBy functions
- New *ordered_merge* function
- Add flexible *comparison* instance methods eq, ne, lt, gt, etc. to DataFrame, Series
- Improve *scatter_matrix* plotting function and add histogram or kernel density estimates to diagonal
- Add *'kde'* plot option for density plots
- Support for converting DataFrame to R data.frame through rpy2
- Improved support for complex numbers in Series and DataFrame
- Add *pct_change* method to all data structures
- Add max_colwidth configuration option for DataFrame console output
- *Interpolate* Series values using index values
- Can select multiple columns from GroupBy
- Add *update* methods to Series/DataFrame for updating values in place
- Add `any` and `all` method to DataFrame

New plotting methods

```
import pandas as pd

fx = pd.read_pickle("data/fx_prices")
import matplotlib.pyplot as plt
```

`Series.plot` now supports a `secondary_y` option:

```
plt.figure()

fx["FR"].plot(style="g")

fx["IT"].plot(style="k--", secondary_y=True)
```

Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, `'kde'` is a new option:

```
In [1]: s = pd.Series(
   ...:     np.concatenate((np.random.randn(1000), np.random.randn(1000) * 0.5 + 3))
   ...: )
   ...:

In [2]: plt.figure()
Out[2]: <Figure size 640x480 with 0 Axes>

In [3]: s.hist(density=True, alpha=0.2)
Out[3]: <AxesSubplot:>

In [4]: s.plot(kind="kde")
Out[4]: <AxesSubplot:ylabel='Density'>
```

See *the plotting page* for much more.

Other API changes

- Deprecation of `offset`, `time_rule`, and `timeRule` arguments names in time series functions. Warnings will be printed until pandas 0.9 or 1.0.

Potential porting issues for pandas <= 0.7.3 users

The major change that may affect you in pandas 0.8.0 is that time series indexes use NumPy's `datetime64` data type instead of `dtype=object` arrays of Python's built-in `datetime.datetime` objects. `DateRange` has been replaced by `DatetimeIndex` but otherwise behaved identically. But, if you have code that converts `DateRange` or `Index` objects that used to contain `datetime.datetime` values to plain NumPy arrays, you may have bugs lurking with code using scalar values because you are handing control over to NumPy:

```
In [5]: import datetime

In [6]: rng = pd.date_range("1/1/2000", periods=10)

In [7]: rng[5]
Out[7]: Timestamp('2000-01-06 00:00:00', freq='D')

In [8]: isinstance(rng[5], datetime.datetime)
Out[8]: True

In [9]: rng_asarray = np.asarray(rng)

In [10]: scalar_val = rng_asarray[5]

In [11]: type(scalar_val)
Out[11]: numpy.datetime64
```

pandas's `Timestamp` object is a subclass of `datetime.datetime` that has nanosecond support (the `nanosecond` field store the nanosecond value between 0 and 999). It should substitute directly into any code that used `datetime.datetime` values before. Thus, I recommend not casting `DatetimeIndex` to regular NumPy arrays.

If you have code that requires an array of `datetime.datetime` objects, you have a couple of options. First, the `astype(object)` method of `DatetimeIndex` produces an array of `Timestamp` objects:

```
In [12]: stamp_array = rng.astype(object)

In [13]: stamp_array
Out[13]:
Index([2000-01-01 00:00:00, 2000-01-02 00:00:00, 2000-01-03 00:00:00,
       2000-01-04 00:00:00, 2000-01-05 00:00:00, 2000-01-06 00:00:00,
       2000-01-07 00:00:00, 2000-01-08 00:00:00, 2000-01-09 00:00:00,
       2000-01-10 00:00:00],
      dtype='object')

In [14]: stamp_array[5]
Out[14]: Timestamp('2000-01-06 00:00:00', freq='D')
```

To get an array of proper `datetime.datetime` objects, use the `to_pydatetime` method:

```
In [15]: dt_array = rng.to_pydatetime()

In [16]: dt_array
Out[16]:
array([datetime.datetime(2000, 1, 1, 0, 0),
       datetime.datetime(2000, 1, 2, 0, 0),
       datetime.datetime(2000, 1, 3, 0, 0),
       datetime.datetime(2000, 1, 4, 0, 0),
       datetime.datetime(2000, 1, 5, 0, 0),
       datetime.datetime(2000, 1, 6, 0, 0),
       datetime.datetime(2000, 1, 7, 0, 0),
       datetime.datetime(2000, 1, 8, 0, 0),
       datetime.datetime(2000, 1, 9, 0, 0),
       datetime.datetime(2000, 1, 10, 0, 0)], dtype=object)

In [17]: dt_array[5]
Out[17]: datetime.datetime(2000, 1, 6, 0, 0)
```

matplotlib knows how to handle `datetime.datetime` but not Timestamp objects. While I recommend that you plot time series using `TimeSeries.plot`, you can either use `to_pydatetime` or register a converter for the Timestamp type. See matplotlib documentation for more on this.

Warning: There are bugs in the user-facing API with the nanosecond datetime64 unit in NumPy 1.6. In particular, the string version of the array shows garbage values, and conversion to `dtype=object` is similarly broken.

```
In [18]: rng = pd.date_range("1/1/2000", periods=10)

In [19]: rng
Out[19]:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10'],
              dtype='datetime64[ns]', freq='D')

In [20]: np.asarray(rng)
```

```
Out[20]:
array(['2000-01-01T00:00:00.000000000', '2000-01-02T00:00:00.000000000',
       '2000-01-03T00:00:00.000000000', '2000-01-04T00:00:00.000000000',
       '2000-01-05T00:00:00.000000000', '2000-01-06T00:00:00.000000000',
       '2000-01-07T00:00:00.000000000', '2000-01-08T00:00:00.000000000',
       '2000-01-09T00:00:00.000000000', '2000-01-10T00:00:00.000000000'],
      dtype='datetime64[ns]')

In [21]: converted = np.asarray(rng, dtype=object)

In [22]: converted[5]
Out[22]: Timestamp('2000-01-06 00:00:00', freq='D')
```

Trust me: don't panic. If you are using NumPy 1.6 and restrict your interaction with `datetime64` values to pandas's API you will be just fine. There is nothing wrong with the data-type (a 64-bit integer internally); all of the important data processing happens in pandas and is heavily tested. I strongly recommend that you **do not work directly with datetime64 arrays in NumPy 1.6** and only use the pandas API.

Support for non-unique indexes: In the latter case, you may have code inside a `try:... catch:` block that failed due to the index not being unique. In many cases it will no longer fail (some method like `append` still check for uniqueness unless disabled). However, all is not lost: you can inspect `index.is_unique` and raise an exception explicitly if it is `False` or go to a different code branch.

Contributors

A total of 27 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Adam Klein
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- David Zaslavsky +
- Eric Chlebek +
- Jacques Kvam
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- thuske +
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5.22 Version 0.7

5.22.1 Version 0.7.3 (April 12, 2012)

This is a minor release from 0.7.2 and fixes many minor bugs and adds a number of nice new features. There are also a couple of API changes to note; these should not affect very many users, and we are inclined to call them "bug fixes" even though they do constitute a change in behavior. See the *full release notes* or issue tracker on GitHub for a complete list.

New features

- New *fixed width file reader*, `read_fwf`
- New *scatter_matrix* function for making a scatter plot matrix

```
from pandas.tools.plotting import scatter_matrix

scatter_matrix(df, alpha=0.2)  # noqa F821
```

- Add `stacked` argument to Series and DataFrame's `plot` method for *stacked bar plots*.

```
df.plot(kind="bar", stacked=True)  # noqa F821
```

```
df.plot(kind="barh", stacked=True)  # noqa F821
```

- Add log x and y *scaling options* to `DataFrame.plot` and `Series.plot`
- Add `kurt` methods to Series and DataFrame for computing kurtosis

NA boolean comparison API change

Reverted some changes to how NA values (represented typically as `NaN` or `None`) are handled in non-numeric Series:

```
In [1]: series = pd.Series(["Steve", np.nan, "Joe"])

In [2]: series == "Steve"
Out[2]:
0     True
1    False
2    False
Length: 3, dtype: bool

In [3]: series != "Steve"
Out[3]:
0    False
1     True
2     True
Length: 3, dtype: bool
```

In comparisons, NA / NaN will always come through as `False` except with `!=` which is `True`. *Be very careful* with boolean arithmetic, especially negation, in the presence of NA data. You may wish to add an explicit NA filter into boolean array operations if you are worried about this:

```
In [4]: mask = series == "Steve"

In [5]: series[mask & series.notnull()]
Out[5]:
0    Steve
Length: 1, dtype: object
```

While propagating NA in comparisons may seem like the right behavior to some users (and you could argue on purely technical grounds that this is the right thing to do), the evaluation was made that propagating NA everywhere, including in numerical arrays, would cause a large amount of problems for users. Thus, a "practicality beats purity" approach was taken. This issue may be revisited at some point in the future.

Other API changes

When calling `apply` on a grouped Series, the return value will also be a Series, to be more consistent with the `groupby` behavior with DataFrame:

```
In [6]: df = pd.DataFrame(
   ...:     {
   ...:         "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],
   ...:         "B": ["one", "one", "two", "three", "two", "two", "one", "three"],
   ...:         "C": np.random.randn(8),
   ...:         "D": np.random.randn(8),
   ...:     }
   ...: )
   ...:

In [7]: df
Out[7]:
     A      B         C         D
0  foo    one  0.469112 -0.861849
1  bar    one -0.282863 -2.104569
```

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```
2  foo    two -1.509059 -0.494929
3  bar  three -1.135632  1.071804
4  foo    two  1.212112  0.721555
5  bar    two -0.173215 -0.706771
6  foo    one  0.119209 -1.039575
7  foo  three -1.044236  0.271860

[8 rows x 4 columns]

In [8]: grouped = df.groupby("A")["C"]

In [9]: grouped.describe()
Out[9]:
     count      mean       std       min       25%       50%       75%       max
A
bar    3.0 -0.530570  0.526860 -1.135632 -0.709248 -0.282863 -0.228039 -0.173215
foo    5.0 -0.150572  1.113308 -1.509059 -1.044236  0.119209  0.469112  1.212112

[2 rows x 8 columns]

In [10]: grouped.apply(lambda x: x.sort_values()[-2:])  # top 2 values
Out[10]:
A
bar  1   -0.282863
     5   -0.173215
foo  0    0.469112
     4    1.212112
Name: C, Length: 4, dtype: float64
```

Contributors

A total of 15 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Abraham Flaxman +
- Adam Klein
- Andreas H. +
- Chang She
- Dieter Vandenbussche
- Jacques Kvam +
- K.-Michael Aye +
- Kamil Kisiel +
- Martin Blais +
- Skipper Seabold
- Thomas Kluyver
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko

- lgautier +

5.22.2 Version 0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

New features

- Add additional tie-breaking methods in DataFrame.rank (GH874)
- Add ascending parameter to rank in Series, DataFrame (GH875)
- Add coerce_float option to DataFrame.from_records (GH893)
- Add sort_columns parameter to allow unsorted plots (GH918)
- Enable column access via attributes on GroupBy (GH882)
- Can pass dict of values to DataFrame.fillna (GH661)
- Can select multiple hierarchical groups by passing list of values in .ix (GH134)
- Add `axis` option to DataFrame.fillna (GH174)
- Add level keyword to `drop` for dropping values from a level (GH159)

Performance improvements

- Use khash for Series.value_counts, add raw function to algorithms.py (GH861)
- Intercept __builtin__.sum in groupby (GH885)

Contributors

A total of 12 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Adam Klein
- Benjamin Gross +
- Dan Birken +
- Dieter Vandenbussche
- Josh +
- Thomas Kluyver
- Travis N. Vaught +
- Wes McKinney
- Wouter Overmeire
- claudiobertoldi +
- elpres +
- joshuaar +

5.22.3 Version 0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.

New features

- Add `to_clipboard` function to pandas namespace for writing objects to the system clipboard (GH774)
- Add `itertuples` method to DataFrame for iterating through the rows of a dataframe as tuples (GH818)
- Add ability to pass fill_value and method to DataFrame and Series align method (GH806, GH807)
- Add fill_value option to reindex, align methods (GH784)
- Enable concat to produce DataFrame from Series (GH787)
- Add `between` method to Series (GH802)
- Add HTML representation hook to DataFrame for the IPython HTML notebook (GH773)
- Support for reading Excel 2007 XML documents using openpyxl

Performance improvements

- Improve performance and memory usage of fillna on DataFrame
- Can concatenate a list of Series along axis=1 to obtain a DataFrame (GH787)

Contributors

A total of 9 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Adam Klein
- Brian Granger +
- Chang She
- Dieter Vandenbussche
- Josh Klein
- Steve +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko

5.22.4 Version 0.7.0 (February 9, 2012)

New features

- New unified *merge function* for efficiently performing full gamut of database / relational-algebra operations. Refactored existing join methods to use the new infrastructure, resulting in substantial performance gains (GH220, GH249, GH267)
- New *unified concatenation function* for concatenating Series, DataFrame or Panel objects along an axis. Can form union or intersection of the other axes. Improves performance of `Series.append` and `DataFrame.append` (GH468, GH479, GH273)
- *Can* pass multiple DataFrames to `DataFrame.append` to concatenate (stack) and multiple Series to `Series.append` too
- *Can* pass list of dicts (e.g., a list of JSON objects) to DataFrame constructor (GH526)
- You can now *set multiple columns* in a DataFrame via `__getitem__`, useful for transformation (GH342)
- Handle differently-indexed output values in `DataFrame.apply` (GH498)

```
In [1]: df = pd.DataFrame(np.random.randn(10, 4))

In [2]: df.apply(lambda x: x.describe())
Out[2]:
                0          1          2          3
count  10.000000  10.000000  10.000000  10.000000
mean    0.190912  -0.395125  -0.731920  -0.403130
std     0.730951   0.813266   1.112016   0.961912
min    -0.861849  -2.104569  -1.776904  -1.469388
25%    -0.411391  -0.698728  -1.501401  -1.076610
50%     0.380863  -0.228039  -1.191943  -1.004091
75%     0.658444   0.057974  -0.034326   0.461706
max     1.212112   0.577046   1.643563   1.071804

[8 rows x 4 columns]
```

- *Add* `reorder_levels` method to Series and DataFrame (GH534)
- *Add* dict-like `get` function to DataFrame and Panel (GH521)
- *Add* `DataFrame.iterrows` method for efficiently iterating through the rows of a DataFrame
- Add `DataFrame.to_panel` with code adapted from `LongPanel.to_long`
- *Add* `reindex_axis` method added to DataFrame
- *Add* `level` option to binary arithmetic functions on `DataFrame` and `Series`
- *Add* `level` option to the `reindex` and `align` methods on Series and DataFrame for broadcasting values across a level (GH542, GH552, others)
- Add attribute-based item access to `Panel` and add IPython completion (GH563)
- *Add* `logy` option to `Series.plot` for log-scaling on the Y axis
- *Add* `index` and `header` options to `DataFrame.to_string`
- *Can* pass multiple DataFrames to `DataFrame.join` to join on index (GH115)
- *Can* pass multiple Panels to `Panel.join` (GH115)
- *Added* `justify` argument to `DataFrame.to_string` to allow different alignment of column headers

- *Add* `sort` option to GroupBy to allow disabling sorting of the group keys for potential speedups (GH595)
- *Can* pass MaskedArray to Series constructor (GH563)
- Add Panel item access via attributes and IPython completion (GH554)
- Implement `DataFrame.lookup`, fancy-indexing analogue for retrieving values given a sequence of row and column labels (GH338)
- Can pass a *list of functions* to aggregate with groupby on a DataFrame, yielding an aggregated result with hierarchical columns (GH166)
- Can call `cummin` and `cummax` on Series and DataFrame to get cumulative minimum and maximum, respectively (GH647)
- `value_range` added as utility function to get min and max of a dataframe (GH288)
- Added `encoding` argument to `read_csv`, `read_table`, `to_csv` and `from_csv` for non-ascii text (GH717)
- *Added* `abs` method to pandas objects
- *Added* `crosstab` function for easily computing frequency tables
- *Added* `isin` method to index objects
- *Added* `level` argument to `xs` method of DataFrame.

API changes to integer indexing

One of the potentially riskiest API changes in 0.7.0, but also one of the most important, was a complete review of how **integer indexes** are handled with regard to label-based indexing. Here is an example:

```
In [3]: s = pd.Series(np.random.randn(10), index=range(0, 20, 2))

In [4]: s
Out[4]:
0    -1.294524
2     0.413738
4     0.276662
6    -0.472035
8    -0.013960
10   -0.362543
12   -0.006154
14   -0.923061
16    0.895717
18    0.805244
Length: 10, dtype: float64

In [5]: s[0]
Out[5]: -1.2945235902555294

In [6]: s[2]
Out[6]: 0.41373810535784006

In [7]: s[4]
Out[7]: 0.2766617129497566
```

This is all exactly identical to the behavior before. However, if you ask for a key **not** contained in the Series, in versions 0.6.1 and prior, Series would *fall back* on a location-based lookup. This now raises a `KeyError`:

```
In [2]: s[1]
KeyError: 1
```

This change also has the same impact on DataFrame:

```
In [3]: df = pd.DataFrame(np.random.randn(8, 4), index=range(0, 16, 2))

In [4]: df
     0        1       2       3
0   0.88427  0.3363 -0.1787  0.03162
2   0.14451 -0.1415  0.2504  0.58374
4  -1.44779 -0.9186 -1.4996  0.27163
6  -0.26598 -2.4184 -0.2658  0.11503
8  -0.58776  0.3144 -0.8566  0.61941
10  0.10940 -0.7175 -1.0108  0.47990
12 -1.16919 -0.3087 -0.6049 -0.43544
14 -0.07337  0.3410  0.0424 -0.16037

In [5]: df.ix[3]
KeyError: 3
```

In order to support purely integer-based indexing, the following methods have been added:

Method	Description
`Series.iget_value(i)`	Retrieve value stored at location `i`
`Series.iget(i)`	Alias for `iget_value`
`DataFrame.irow(i)`	Retrieve the `i`-th row
`DataFrame.icol(j)`	Retrieve the `j`-th column
`DataFrame.iget_value(i, j)`	Retrieve the value at row `i` and column `j`

API tweaks regarding label-based slicing

Label-based slicing using `ix` now requires that the index be sorted (monotonic) **unless** both the start and endpoint are contained in the index:

```
In [1]: s = pd.Series(np.random.randn(6), index=list('gmkaec'))

In [2]: s
Out[2]:
g   -1.182230
m   -0.276183
k   -0.243550
a    1.628992
e    0.073308
c   -0.539890
dtype: float64
```

Then this is OK:

```
In [3]: s.ix['k':'e']
Out[3]:
k   -0.243550
a    1.628992
e    0.073308
dtype: float64
```

But this is not:

```
In [12]: s.ix['b':'h']
KeyError 'b'
```

If the index had been sorted, the "range selection" would have been possible:

```
In [4]: s2 = s.sort_index()

In [5]: s2
Out[5]:
a    1.628992
c   -0.539890
e    0.073308
g   -1.182230
k   -0.243550
m   -0.276183
dtype: float64

In [6]: s2.ix['b':'h']
Out[6]:
c   -0.539890
e    0.073308
g   -1.182230
dtype: float64
```

Changes to Series `[]` operator

As as notational convenience, you can pass a sequence of labels or a label slice to a Series when getting and setting values via `[]` (i.e. the `__getitem__` and `__setitem__` methods). The behavior will be the same as passing similar input to `ix` **except in the case of integer indexing**:

```
In [8]: s = pd.Series(np.random.randn(6), index=list('acegkm'))

In [9]: s
Out[9]:
a   -1.206412
c    2.565646
e    1.431256
g    1.340309
k   -1.170299
m   -0.226169
Length: 6, dtype: float64

In [10]: s[['m', 'a', 'c', 'e']]
Out[10]:
m   -0.226169
a   -1.206412
c    2.565646
e    1.431256
Length: 4, dtype: float64

In [11]: s['b':'l']
Out[11]:
c    2.565646
e    1.431256
```

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```
g    1.340309
k   -1.170299
Length: 4, dtype: float64

In [12]: s['c':'k']
Out[12]:
c    2.565646
e    1.431256
g    1.340309
k   -1.170299
Length: 4, dtype: float64
```

In the case of integer indexes, the behavior will be exactly as before (shadowing `ndarray`):

```
In [13]: s = pd.Series(np.random.randn(6), index=range(0, 12, 2))

In [14]: s[[4, 0, 2]]
Out[14]:
4    0.132003
0    0.410835
2    0.813850
Length: 3, dtype: float64

In [15]: s[1:5]
Out[15]:
2    0.813850
4    0.132003
6   -0.827317
8   -0.076467
Length: 4, dtype: float64
```

If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

Other API changes

- The deprecated `LongPanel` class has been completely removed
- If `Series.sort` is called on a column of a DataFrame, an exception will now be raised. Before it was possible to accidentally mutate a DataFrame's column by doing `df[col].sort()` instead of the side-effect free method `df[col].order()` (GH316)
- Miscellaneous renames and deprecations which will (harmlessly) raise `FutureWarning`
- `drop` added as an optional parameter to `DataFrame.reset_index` (GH699)

Performance improvements

- *Cythonized GroupBy aggregations* no longer presort the data, thus achieving a significant speedup (GH93). GroupBy aggregations with Python functions significantly sped up by clever manipulation of the ndarray data type in Cython (GH496).
- Better error message in DataFrame constructor when passed column labels don't match data (GH497)
- Substantially improve performance of multi-GroupBy aggregation when a Python function is passed, reuse ndarray object in Cython (GH496)
- Can store objects indexed by tuples and floats in HDFStore (GH492)

- Don't print length by default in Series.to_string, add `length` option (GH489)
- Improve Cython code for multi-groupby to aggregate without having to sort the data (GH93)
- Improve MultiIndex reindexing speed by storing tuples in the MultiIndex, test for backwards unpickling compatibility
- Improve column reindexing performance by using specialized Cython take function
- Further performance tweaking of Series.__getitem__ for standard use cases
- Avoid Index dict creation in some cases (i.e. when getting slices, etc.), regression from prior versions
- Friendlier error message in setup.py if NumPy not installed
- Use common set of NA-handling operations (sum, mean, etc.) in Panel class also (GH536)
- Default name assignment when calling `reset_index` on DataFrame with a regular (non-hierarchical) index (GH476)
- Use Cythonized groupers when possible in Series/DataFrame stat ops with `level` parameter passed (GH545)
- Ported skiplist data structure to C to speed up `rolling_median` by about 5-10x in most typical use cases (GH374)

Contributors

A total of 18 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Adam Klein
- Bayle Shanks +
- Chris Billington +
- Dieter Vandenbussche
- Fabrizio Pollastri +
- Graham Taylor +
- Gregg Lind +
- Josh Klein +
- Luca Beltrame
- Olivier Grisel +
- Skipper Seabold
- Thomas Kluyver
- Thomas Wiecki +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
- fabriziop +
- theandygross +

5.23 Version 0.6

5.23.1 Version 0.6.1 (December 13, 2011)

New features

- Can *append single rows* (as Series) to a DataFrame
- Add Spearman and Kendall rank *correlation* options to Series.corr and DataFrame.corr (GH428)
- *Added* `get_value` and `set_value` methods to Series, DataFrame, and Panel for very low-overhead access (>2x faster in many cases) to scalar elements (GH437, GH438). `set_value` is capable of producing an enlarged object.
- Add PyQt table widget to sandbox (GH435)
- DataFrame.align can *accept Series arguments* and an *axis option* (GH461)
- Implement new *SparseArray* and `SparseList` data structures. SparseSeries now derives from SparseArray (GH463)
- *Better console printing options* (GH453)
- Implement fast *data ranking* for Series and DataFrame, fast versions of scipy.stats.rankdata (GH428)
- Implement `DataFrame.from_items` alternate constructor (GH444)
- DataFrame.convert_objects method for *inferring better dtypes* for object columns (GH302)
- Add *rolling_corr_pairwise* function for computing Panel of correlation matrices (GH189)
- Add *margins* option to *pivot_table* for computing subgroup aggregates (GH114)
- Add `Series.from_csv` function (GH482)
- *Can pass* DataFrame/DataFrame and DataFrame/Series to rolling_corr/rolling_cov (GH #462)
- MultiIndex.get_level_values can *accept the level name*

Performance improvements

- Improve memory usage of `DataFrame.describe` (do not copy data unnecessarily) (PR #425)
- Optimize scalar value lookups in the general case by 25% or more in Series and DataFrame
- Fix performance regression in cross-sectional count in DataFrame, affecting DataFrame.dropna speed
- Column deletion in DataFrame copies no data (computes views on blocks) (GH #158)

Contributors

A total of 7 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Dieter Vandenbussche
- Fernando Perez +
- Jev Kuznetsov +
- Joon Ro

- Ralph Bean +
- Wes McKinney
- Wouter Overmeire

5.23.2 Version 0.6.0 (November 25, 2011)

New features

- *Added* `melt` function to `pandas.core.reshape`
- *Added* `level` parameter to group by level in Series and DataFrame descriptive statistics (GH313)
- *Added* `head` and `tail` methods to Series, analogous to DataFrame (GH296)
- *Added* `Series.isin` function which checks if each value is contained in a passed sequence (GH289)
- *Added* `float_format` option to `Series.to_string`
- *Added* `skip_footer` (GH291) and `converters` (GH343) options to `read_csv` and `read_table`
- *Added* `drop_duplicates` and `duplicated` functions for removing duplicate DataFrame rows and checking for duplicate rows, respectively (GH319)
- *Implemented* operators '&', '|', '^', '-' on DataFrame (GH347)
- *Added* `Series.mad`, mean absolute deviation
- *Added* `QuarterEnd` DateOffset (GH321)
- *Added* `dot` to DataFrame (GH65)
- Added `orient` option to `Panel.from_dict` (GH359, GH301)
- *Added* `orient` option to `DataFrame.from_dict`
- *Added* passing list of tuples or list of lists to `DataFrame.from_records` (GH357)
- *Added* multiple levels to groupby (GH103)
- *Allow* multiple columns in `by` argument of `DataFrame.sort_index` (GH92, GH362)
- *Added* fast `get_value` and `put_value` methods to DataFrame (GH360)
- *Added* `cov` instance methods to Series and DataFrame (GH194, GH362)
- *Added* `kind='bar'` option to `DataFrame.plot` (GH348)
- *Added* `idxmin` and `idxmax` to Series and DataFrame (GH286)
- *Added* `read_clipboard` function to parse DataFrame from clipboard (GH300)
- *Added* `nunique` function to Series for counting unique elements (GH297)
- *Made* DataFrame constructor use Series name if no columns passed (GH373)
- *Support* regular expressions in read_table/read_csv (GH364)
- *Added* `DataFrame.to_html` for writing DataFrame to HTML (GH387)
- *Added* support for MaskedArray data in DataFrame, masked values converted to NaN (GH396)
- *Added* `DataFrame.boxplot` function (GH368)
- *Can* pass extra args, kwds to DataFrame.apply (GH376)
- *Implement* `DataFrame.join` with vector `on` argument (GH312)

- *Added* `legend` boolean flag to `DataFrame.plot` (GH324)
- *Can* pass multiple levels to `stack` and `unstack` (GH370)
- *Can* pass multiple values columns to `pivot_table` (GH381)
- *Use* Series name in GroupBy for result index (GH363)
- *Added* `raw` option to `DataFrame.apply` for performance if only need ndarray (GH309)
- Added proper, tested weighted least squares to standard and panel OLS (GH303)

Performance enhancements

- VBENCH Cythonized `cache_readonly`, resulting in substantial micro-performance enhancements throughout the code base (GH361)
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations with 3-5x better performance than `np.apply_along_axis` (GH309)
- VBENCH Improved performance of `MultiIndex.from_tuples`
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations
- VBENCH + DOCUMENT Add `raw` option to `DataFrame.apply` for getting better performance when
- VBENCH Faster cythonized count by level in Series and DataFrame (GH341)
- VBENCH? Significant GroupBy performance enhancement with multiple keys with many "empty" combinations
- VBENCH New Cython vectorized function `map_infer` speeds up `Series.apply` and `Series.map` significantly when passed elementwise Python function, motivated by (GH355)
- VBENCH Significantly improved performance of `Series.order`, which also makes np.unique called on a Series faster (GH327)
- VBENCH Vastly improved performance of GroupBy on axes with a MultiIndex (GH299)

Contributors

A total of 8 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Adam Klein +
- Chang She +
- Dieter Vandenbussche
- Jeff Hammerbacher +
- Nathan Pinger +
- Thomas Kluyver
- Wes McKinney
- Wouter Overmeire +

5.24 Version 0.5

5.24.1 Version 0.5.0 (October 24, 2011)

New features

- *Added* `DataFrame.align` method with standard join options
- *Added* `parse_dates` option to `read_csv` and `read_table` methods to optionally try to parse dates in the index columns
- *Added* `nrows`, `chunksize`, and `iterator` arguments to `read_csv` and `read_table`. The last two return a new `TextParser` class capable of lazily iterating through chunks of a flat file (GH242)
- *Added* ability to join on multiple columns in `DataFrame.join` (GH214)
- Added private `_get_duplicates` function to `Index` for identifying duplicate values more easily (ENH5c)
- *Added* column attribute access to DataFrame.
- *Added* Python tab completion hook for DataFrame columns. (GH233, GH230)
- *Implemented* `Series.describe` for Series containing objects (GH241)
- *Added* inner join option to `DataFrame.join` when joining on key(s) (GH248)
- *Implemented* selecting DataFrame columns by passing a list to `__getitem__` (GH253)
- *Implemented* & and | to intersect / union Index objects, respectively (GH261)
- *Added* `pivot_table` convenience function to pandas namespace (GH234)
- *Implemented* `Panel.rename_axis` function (GH243)
- DataFrame will show index level names in console output (GH334)
- *Implemented* `Panel.take`
- *Added* `set_eng_float_format` for alternate DataFrame floating point string formatting (ENH61)
- *Added* convenience `set_index` function for creating a DataFrame index from its existing columns
- *Implemented* `groupby` hierarchical index level name (GH223)
- *Added* support for different delimiters in `DataFrame.to_csv` (GH244)
- TODO: DOCS ABOUT TAKE METHODS

Performance enhancements

- VBENCH Major performance improvements in file parsing functions `read_csv` and `read_table`
- VBENCH Added Cython function for converting tuples to ndarray very fast. Speeds up many MultiIndex-related operations
- VBENCH Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance (GH211)
- VBENCH Improved speed of `DataFrame.xs` on mixed-type DataFrame objects by about 5x, regression from 0.3.0 (GH215)
- VBENCH With new `DataFrame.align` method, speeding up binary operations between differently-indexed DataFrame objects by 10-25%.

- VBENCH Significantly sped up conversion of nested dict into DataFrame (GH212)
- VBENCH Significantly speed up DataFrame `__repr__` and `count` on large mixed-type DataFrame objects

Contributors

A total of 9 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Aman Thakral +
- Luca Beltrame +
- Nick Pentreath +
- Skipper Seabold
- Thomas Kluyver +
- Wes McKinney
- Yaroslav Halchenko +
- lodagro +
- unknown +

5.25 Version 0.4

5.25.1 Versions 0.4.1 through 0.4.3 (September 25 - October 9, 2011)

New features

- Added Python 3 support using 2to3 (GH200)
- *Added* `name` attribute to `Series`, now prints as part of `Series.__repr__`
- *Added* instance methods `isnull` and `notnull` to Series (GH209, GH203)
- *Added* `Series.align` method for aligning two series with choice of join method (ENH56)
- *Added* method `get_level_values` to `MultiIndex` (GH188)
- Set values in mixed-type `DataFrame` objects via `.ix` indexing attribute (GH135)
- Added new `DataFrame` *methods* `get_dtype_counts` and property `dtypes` (ENHdc)
- Added *ignore_index* option to `DataFrame.append` to stack DataFrames (ENH1b)
- `read_csv` tries to *sniff* delimiters using `csv.Sniffer` (GH146)
- `read_csv` can *read* multiple columns into a `MultiIndex`; DataFrame's `to_csv` method writes out a corresponding `MultiIndex` (GH151)
- `DataFrame.rename` has a new `copy` parameter to *rename* a DataFrame in place (ENHed)
- *Enable* unstacking by name (GH142)
- *Enable* `sortlevel` to work by level (GH141)

Performance enhancements

- Altered binary operations on differently-indexed SparseSeries objects to use the integer-based (dense) alignment logic which is faster with a larger number of blocks (GH205)
- Wrote faster Cython data alignment / merging routines resulting in substantial speed increases
- Improved performance of `isnull` and `notnull`, a regression from v0.3.0 (GH187)
- Refactored code related to `DataFrame.join` so that intermediate aligned copies of the data in each `DataFrame` argument do not need to be created. Substantial performance increases result (GH176)
- Substantially improved performance of generic `Index.intersection` and `Index.union`
- Implemented `BlockManager.take` resulting in significantly faster `take` performance on mixed-type `DataFrame` objects (GH104)
- Improved performance of `Series.sort_index`
- Significant groupby performance enhancement: removed unnecessary integrity checks in DataFrame internals that were slowing down slicing operations to retrieve groups
- Optimized `_ensure_index` function resulting in performance savings in type-checking Index objects
- Wrote fast time series merging / joining methods in Cython. Will be integrated later into DataFrame.join and related functions

Contributors

A total of 2 people contributed patches to this release. People with a "+" by their names contributed a patch for the first time.

- Thomas Kluyver +
- Wes McKinney

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